Université Paris Nanterre
200 av. de la République
92001 Nanterre Cedex
www.parisnanterre.fr

École Doctorale 396 : Économie, Organisation, Société
EconomiX - UMR 7235

Membre de l'université Paris Lumières

Aurélien Quignon

Essays on the Economics of Innovation

Thèse présentée et soutenue publiquement le 03/12/2020
en vue de l'obtention du doctorat de Sciences économiques de l'Université Paris Nanterre
sous la direction de Mme Nadine Levratto (Université Paris Nanterre)

Jury * :

Rapporteur :	M. Michele Cincera	Professeur des Universités, Université Libre de Bruxelles
Rapporteure :	Mme. Jackie Krafft	Directrice de Recherche, CNRS
Membre du jury :	Mme. Corinne Autant-Bernard	Professeure des Universités, GATE Lyon-St-Etienne
Membre du jury :	M. Jacques Mairesse	Professeur des Universités, Université de Maastricht, CREST (ENSAE)
Membre du jury :	M. Saïd Souam	Professeur des Universités, Université Paris Nanterre

Université Paris Nanterre

École doctorale : ED 396 – Économie, Organisations, Société

THÈSE

pour obtenir le grade de
Docteur en Sciences Économiques

Présentée et soutenue publiquement le 3 décembre 2020 par

Aurélien Quignon

Essays on the Economics of Innovation

Doctorat de l'Université Paris Nanterre,
sous la direction de Nadine Levratto

Composition du jury :

Rapporteurs

Michele Cincera	Professeur, Université Libre de Bruxelles
Jackie Krafft	Directrice de Recherche, Université Côte d'Azur

Examinateurs

Corrine Autant-Bernard	Professeure, CNRS, GATE Lyon-St Etienne
Jacques Mairesse	Professeur, Université de Maastricht, CREST-ENSAE
Saïd Souam	Professeur, Université Paris Nanterre

Directeur

Nadine Levratto	Directrice de Recherche, CNRS, Université Paris Nanterre

General Outline / Plan d’Ensemble

Remerciements

Je tiens tout d'abord à exprimer mes remerciements à Nadine Levratto, qui a encadré mon travail doctoral lors de ces trois années. J'ai eu la chance de bénéficier de ses conseils scientifiques continus, de son soutien et de ses nombreuses relectures, sans lesquelles il m'aurait été impossible de mener à bien mon projet de thèse.

Je souhaitais également exprimer ma gratitude à Mmes Corinne Autant-Bernard, Jackie Krafft et MM. Michele Cincera, Jacques Mairesse et Saïd Souam pour avoir accepté de faire partie de mon jury et de consacrer de leur temps précieux à m'aider à améliorer mes travaux de recherche.

Au cours de mon doctorat, j'ai pu bénéficier d'excellentes conditions d'accueil. Tout d'abord au sein de l'Institut Friedland, où j'ai débuté ma thèse. Je remercie chaleureusement Thierry Philipponnat de m'avoir accueilli dans un centre de réflexion qui était au début de son histoire, une histoire trop courte à mes yeux. Thierry m'a permis grâce à sa bienveillance, de mener mon travail dans un environnement intellectuellement stimulant. Je tiens également à remercier Renaud Redien-Collot pour l'ensemble de nos échanges qui m'ont permis de nourrir mes réflexions sur l'innovation d'un point de vue sociologique.

Je remercie également l'ensemble des membres d'EconomiX pour avoir rendu ces trois années de thèses agréables. Merci à Valérie Mignon sans qui je n'aurais jamais entrepris de poursuivre en doctorat. Merci aussi à Frédéric Hammerer pour sa disponibilité et sa réactivité. Je suis reconnaissant envers mes collègues doctorants du Bureau 209, avec qui j'ai eu le plaisir de partager une expérience doctorale très enrichissante, à la fois sur le plan académique que personnel. Je pense particulièrement à Giuseppe Arcuri, Rosalind Bell-Aldeghi, Julien Bergeot, Mathieu Chtioui, Anicet Kabre, Thibault Mirabel, Julien Salin, Penda Sokhna, et Eléazar Zerbo. Une mention spéciale pour Julien, qui a été constamment présent pendant tout le doctorat, pour l'ensemble des discussions (de travail et autres) que nous avons eues au bureau et en dehors. De même, merci à Thibault pour sa bonne humeur et bon courage pour la fin de ta thèse.

Je pense également à mes collègues de l'Institut Friedland, qui m'ont accueilli dans l'équipe, Anne Demay, Serhane Dendani et Laurence Guillot. Une pensée toute particulière pour Serhane, pour l'ensemble de nos discussions sur l'actualité politique, notre passion commune pour le football partagée autour d'un café ou encore pendant les déjeuners.

Sur une note plus personnelle, je suis extrêmement reconnaissant à mes parents et mes amis pour m'avoir fourni un soutien inconditionnel tout au long de mes études supérieures.

Abstract / Résumé

This thesis studies different aspects of the factors that directly or indirectly impact innovative activities both at the macroeconomic and microeconomic levels. In a context where policymakers and firms consider innovation as a strategic asset for productivity growth, this thesis aims at contributing to the literature on the determinants of innovation and related market failures relying on primarily empirical contributions. The first chapter considers the impact of competition and trade openness on innovation. Country innovation intensity positively responds to less stringent regulation, but only domestic product-market reform is directly related to innovation. The second chapter evaluates a European program that supports SME's innovation. R&D grants positively impact patenting, but this effect is stronger for more financially constrained firms by a certification mechanism on the quality of firms. Finally, the third chapter considers the role of information frictions among a crowd-rating framework, on ventures' subsequent success. This chapter uses a novel sample of French ventures at both the idea and seed stage. Taken together, this thesis explores three different instruments that aim to spur innovation intensity, either in terms of R&D, patents, financing, and venture success outcomes.

Keywords : Innovation, R&D, Competition, Financing Constraints

⋆ ⋆ ⋆ ⋆ ⋆

Cette thèse étudie différents aspects concernant les facteurs qui ont un impact direct ou indirect sur les activités innovantes aux niveaux macroéconomique et microéconomique. Dans un contexte où les décideurs politiques et les entreprises considèrent l'innovation comme un atout stratégique pour la croissance de la productivité, cette thèse vise à contribuer à la littérature sur les déterminants de l'innovation et les défaillances du marché associées en s'appuyant principalement sur des contributions empiriques. Le premier chapitre examine l'impact de la concurrence et de l'ouverture commerciale sur l'innovation. L'intensité d'innovation des pays répond positivement à une réglementation moins stricte, mais que seule la réforme intérieure du marché des produits est directement liée à l'innovation. Le deuxième chapitre évalue un programme européen qui soutient l'innovation des PME. Les subventions de R&D ont un impact positif sur les brevets, mais cet effet est plus fort pour les entreprises plus contraintes financièrement par un mécanisme de certification sur la qualité des entreprises. Enfin, le troisième chapitre examine le rôle des frictions informationnelles dans un cadre de notation par la foule, sur le succès ultérieur des startups. Ce chapitre utilise un nouvel échantillon d'entreprises françaises à la fois au stade de l'idée et de la phase de démarrage. Dans l'ensemble, cette thèse explore trois instruments différents qui visent à stimuler l'intensité de l'innovation, que ce soit en termes de R&D, de brevets, de financement et de facteurs de succès des entreprises.

Mots-Clés : Innovation, R&D, Concurrence, Contraintes de Financement

Introduction Générale

Préambule

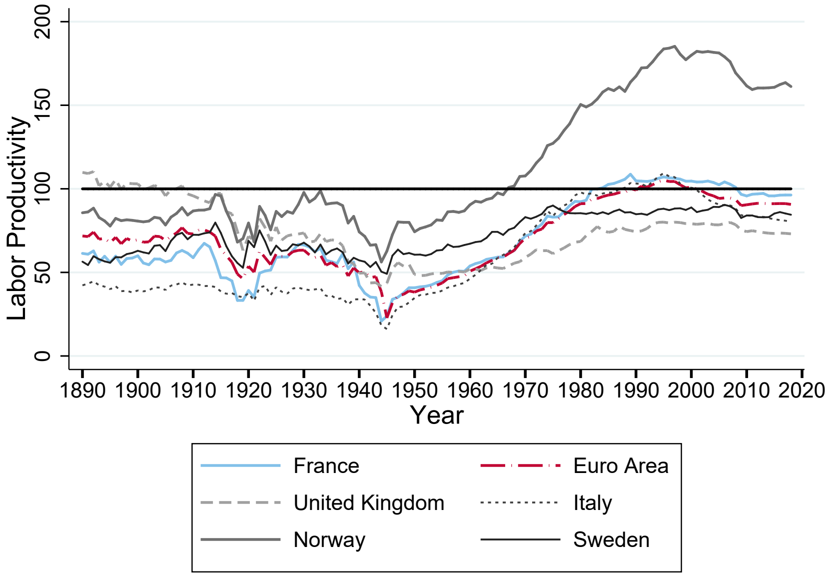
La croissance de la productivité peut être considérée comme un objectif de politique économique légitime. En effet, la productivité est l'un des principaux facteurs d'accroissement du niveau de vie et de croissance, et a ainsi bénéficié d'un grand intérêt dans la littérature économique. Dans les pays industrialisés, la croissance passe principalement par une utilisation plus efficace des facteurs de production, le capital humain et physique, mais également par le progrès technologique. De la fin de la Seconde Guerre mondiale au milieu des années 1990, l'Europe, dont la France, a traversé une période de rattrapage ininterrompue caractérisée par des taux de croissance de la productivité élevé (Figure 1[1]. Depuis, l'économie française a connu une période de ralentissement de la croissance de la productivité, qui a été remarquablement persistante. Cette tendance est également observée dans d'autres pays développés, à l'instar des Etats-Unis. Un tel ralentissement est quelque peu surprenant étant donné l'émergence et la diffusion des technologies de l'information et de la communication (TIC).

Le ralentissement de la croissance de la productivité à partir du milieu des années 1990 peut être observée dans les tendances à long-terme de la productivité du travail par heure et la productivité totale des facteurs[2]. Au cours de cette période jusqu'à la crise financière globale, les schémas de croissance de la productivité entre la France, l'Europe et les États-Unis ont considérablement évolué. Aux États-Unis, nous observons une forte croissance annuelle de la productivité du travail de 1.3% (1995-2004) alors que la tendance s'inverse en Europe, marquant l'interruption du rattrapage européen (Van Ark et al., 2008)[3]. Cependant, depuis la période de la grande récession, la plupart des pays ont connu un ralentissement de la productivité sans schéma de convergence, accompagné

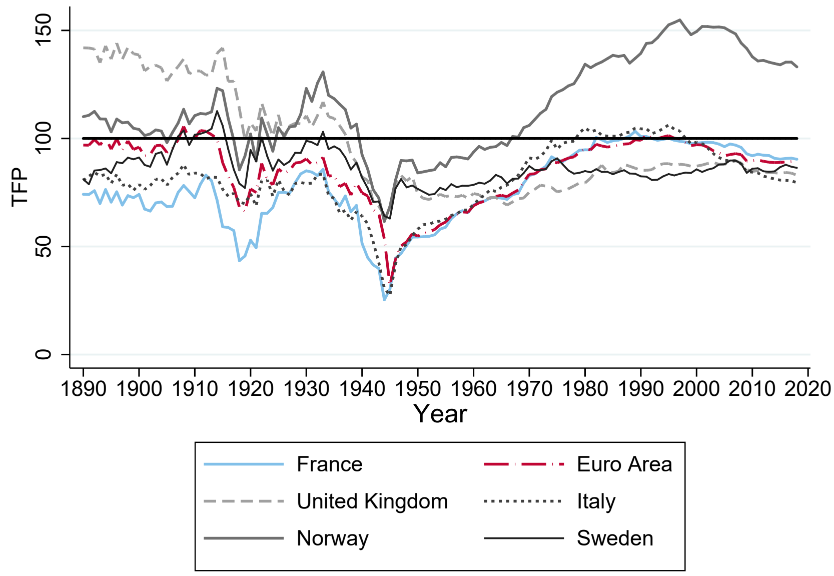
[1]Le processus de convergence nécessite des conditions institutionnelles favorables à l'investissement, et sont résumées dans le concept de *"capacités sociales"* énoncé par Abramovitz et al. (1991). Ces conditions comprennent notamment un environnement économique stable, sécurisé, l'existence de droits de propriété et la disponibilité d'un stock de capital humain.

[2]La productivité du travail est définie comme le ratio du PIB (Y) sur le travail (L), LP=Y/L. En revanche, la productivité totale des facteurs est définie comme le ratio du PIB sur les deux facteurs de production usuels, le travail (L) et le capital (K).

[3]Ces tendances ont été largement soulignées dans la littérature. Une explication potentielle de ce ralentissement de la productivité, mesurée comme le rapport du PIB au travail (le nombre d'heures de travail) peut être liée à un retard de la diffusion du choc technologique des TIC. De nombreuses études ont mis en avant (Bergeaud et al. 2016, Turner and Boulhol 2008 et Aghion et al. 2009) que ce retard dans la diffusion des Tic était dû au faible niveau de qualification de la population active mais également à des niveaux de rigidité sur le marché du travail et des produits plus élevés.



(a)



(b)

Figure 1 – Tendances de la productivité du travail et de la productivité totale des facteurs 1890-2018.

Notes : Cette figure montre dans le panneau A la productivité du travail par heure ($2010 parité de pouvoir d'achat) par rapport au niveau américain actuel dans certains pays européens. Le panneau B montre le niveau de productivité totale des facteurs ($2010 parité de pouvoir d'achat) par rapport au niveau américain actuel. Les deux figures sont relatifs au niveau américain U.S = 100.
Source : (Bergeaud et al., 2016)

d'une baisse des salaires réels et d'une hausse des inégalités[4].

[4]Pour plus de détails sur les statistiques des salaires réels, voir OECD (2019).

Le processus d'innovation et sa capacité à générer de nouvelles idées sont essentiels pour assurer une croissance de la productivité à long terme (Bloom et al., 2019). En effet, nous savons par l'histoire qu'au cours du XXe siècle, se sont produits deux chocs de productivité qui correspondent respectivement à la deuxième révolution technologique et à l'utilisation et à la diffusion des technologies de l'information et de la communication (TIC), des années 1980 jusqu'à présent[5]. Bien qu'il existe un large consensus parmi les universitaires et les décideurs publics, la façon dont le progrès technologique améliore la productivité dépend de nombreux aspects. Pour des pays à la frontière technologique, quelles sont les recours les plus efficients pour stimuler l'effort d'innovation ?

1 L'Economie de la Connaissance et de l'Innovation

1.1 Contexte Général

Après la dévastation du continent européen et de son économie pendant la deuxième guerre mondiale, de nombreux pays ont connu une première période (1950-1973) pendant laquelle la croissance de la productivité du travail fut rapide, accompagné d'un rattrapage en termes de revenu par habitant. Cette accélération est basée sur le recours à de nouvelles technologies et l'innovation incrémentale (Boltho, 1982). En effet, les performances de l'économie française en termes d'innovation sont au centre des préoccupations des décideurs publics. Ainsi, la recherche et la diffusion de nouvelles technologies sont définies comme une initiative fondamentale du deuxième Plan de Modernisation et d'Equipement du Commissariat Général crée le 3 Janvier 1946 :

"Tandis que l'objet essentiel du premier plan a été le développement et la modernisation des secteurs de base qui commandaient tout essor ultérieur de l'activité nationale, le deuxième plan se caractérise par des actions de base – développement de la recherche scientifique et technique, diffusion des méthodes modernes de production, spécialisation et adaptation des entreprises [. . .] – qui doivent assurer le plein emploi de nos ressources humaines et matérielles et faire progresser rapidement la productivité nationale". Deuxième Plan de Modernisation et d'Equipement (1954-57).

[5] Gordon (2012) soutient que le ralentissement de la productivité reflète la baisse des retours sur investissement dans la révolution des TIC, survenue entre les années 1920 et 1930 aux États-Unis, est plus importante que les progrès technologiques récents. En revanche, Syverson (2017) et Byrne et al. (2016) estiment que la baisse de la productivité du travail américaine depuis 2004 n'est pas due à une sous-estimation de la croissance des TIC.

Au-delà du développement de la recherche scientifique et de la diffusion dans l'économie française de méthodes modernes de production, l'objectif du Commissariat Général au Plan est de permettre à la France de rattraper son retard envers les pays développés :

"La France, dont nombre de savants ont été les promoteurs de la science moderne, tend à perdre depuis une cinquantaine d'années la place qu'elle occupait et n'a pas développé ses recherches à l'échelle moderne. Il s'agit de rattraper ce retard" (p78-79, 1956).

Dans la continuité de l'effort de rattrapage formulé dans le deuxième plan de modernisation et d'équipement, la France, soucieuse de développer sa propre légitimité scientifique au niveau international, a promu une politique de soutien à la recherche. Jusqu'en 1970, les efforts se sont concentrés sur le soutien public à la recherche fondamentale et les projets industriels. C'est à partir des années 1980 que les efforts ont été mis au profit de la recherche appliquée afin de valoriser les retombées de la connaissance dans les secteurs industriels. Au cours de cette période, le processus linéaire de l'innovation et les conséquences des interventions publiques sont remis en cause pour progressivement basculer vers une politique d'innovation en faveur du développement technologique des entreprises. Ainsi, de nouvelles politiques publiques se mettent progressivement en place.

Cette volonté d'accroitre les performances d'innovation s'est vue par la suite renforcée au niveau européen. Le Conseil européen de Lisbonne qui s'est tenu en mars 2000 avait fixé pour objectif stratégique que l'Union européenne devienne *"l'économie de la connaissance la plus compétitive et la plus dynamique du monde"* sur la décennie à venir. Afin d'y parvenir, de nombreuses orientations ont été définies, notamment pour favoriser un environnement moteur de l'investissement privé en recherche et développement (R&D, ci-après) et d'innovation, pour accroitre les partenariats de R&D, la dynamique de création et de développement de jeunes entreprises innovantes (start-ups) par le biais de mesures fiscales, l'accès aux fonds de capital-risque ou encore l'instauration d'un environnement réglementaire favorable à la concurrence. Les précédents objectifs ont été par la suite renforcés lors du Conseil européen de Barcelone (mars 2002), mettant l'accent sur l'effort d'innovation afin d'atteindre en 2010 un niveau d'investissement en R&D et innovation de 3% du PIB au sein de l'Union Européenne.

Depuis la création de la Communauté Européenne (1957), l'intention de soutenir la recherche et l'innovation au niveau européen est donc devenu un enjeu central. A cette fin, l'Union Européenne a instauré comme instrument de politique lié à la recherche un ensemble successif de *"Programme-Cadre"*, devenant une composante majeure du financement de la recherche et de l'innovation en Europe. Dans le but de définir une stratégie globale, le premier programme-cadre couvrant une période de trois ans, de 1984 à 1987 a été instauré. Le budget total consacré à ce programme s'élevait à 3,75 milliards d'euros. Successivement, le budget alloué aux différents programmes a augmenté, atteignant 80 milliards d'euros de financement disponible pour le dernier programme en date, instauré en 2014 : Horizon2020 (2014-2020)[6]. Cette tendance à la hausse des financements pour la recherche et l'innovation au cours des trente dernières années traduit l'importance accordée au soutien des entreprises, y compris pour faire face aux défis sociétaux.

1.2 Innovation : Faits Stylisés

En 2010, l'intensité de R&D de l'Union Européenne (à 28 membres) était de 1,83% ; elle a légèrement augmenté jusqu'en 2018, pour s'établir à 2.03% du PIB (Tableau 1). Dix-huit ans après le conseil de Lisbonne, les dépenses de R&D au sein de l'Union Européenne n'ont jamais atteint l'objectif ciblé. Ce constat est équivalent pour la France. Le tableau 1 présente les dépenses de R&D et la R&D en pourcentage du PIB en France et six autres pays retenus à des fins de comparaison. Les dépenses de R&D sont inférieures à celle de l'Allemagne, du Japon, de la Chine et des Etats-Unis ces écarts étant également visibles pour la R&D rapportée au PIB. Seuls l'Allemagne et le Japon ont dépassé le seuil des 3% de dépenses de R&D. En 2018, les dépenses de R&D réalisées en France se sont établies à un peu plus de 68 milliards de dollars ($ US, PPA) (Source : OCDE STI).

La figure 2 montre l'évolution des dépenses de R&D sur le long-terme en France dont elle propose une décomposition par source de financement. Les dépenses intérieures de R&D en pourcentage du PIB sont passées de 1,48% en 1963 à 2,02% en 2018. Même si l'intensité des dépenses de R&D a connu une augmentation de 37% entre 1962 et 1985, depuis cette intensité plafonne autour de 2% du PIB. Au fil du temps, il y a eu pourtant eu une augmentation de la part de la R&D financée par les entreprises alors que dans le même temps, les financements publics ont connu une baisse relative, contribuant 1,7 fois moins que les entreprises[7]. Cependant, le développement des aides fiscales en faveur des entreprises, notamment le nombre d'entreprises déclarant des dépenses au titre du Crédit Impôt Recherche (CIR)[8], a fortement augmenté depuis la précédente réforme survenue

[6]Le programme-cadre Horizon2020 est le huitième programme européen pour la recherche et l'innovation. En 2020, 31 256 projets ont été retenus au niveau européen, pour un total de 57,6 milliards d'euros de subventions allouées.

[7]Cette baisse relative de la R&D financée par le gouvernement rapportée au PIB est similaire aux États-Unis. Depuis 1979, le secteur des entreprises a investi plus que le gouvernement fédéral en R&D (Bloom et al., 2019).

[8]Le CIR est un dispositif central de la politique française de recherche et d'innovation, dont l'objectif

Table 1 –
Comparaison Internationale : 2018

Pays	DIRD ($ US PPA, milliard)	DIRD/PIB (%)
France	68.4	2.2
Royaume-Uni	53.1	1.71
Allemagne	141.4	3.13
Finlande	7.5	2.75
Japon	171.3	3.26
Etats-Unis	581.6	2.83
Chine	554.3	2.19
Union Européenne (28 pays)	464.5	2.03

Notes : Cette figure montre les dépenses intérieures en R&D (DIRD) exprimé en milliard de dollars en parité de pouvoir d'achat et les dépenses intérieures en R&D en pourcentage du PIB du pays domestique pour un ensemble de pays membre de l'OCDE, dont la France ainsi que la moyenne de l'union européenne.
Source : Principaux Indicateurs de la Science et de la Technologie (PIST, 2020)

en 2008. Le nombre d'entreprises bénéficiaires a triplé entre 2007 (9 886) et 2015 (25 597 entreprises) ainsi que les montants attribués, passant de 1,8 milliards €en 2007 à 6.3 milliards €en 2015 (Source : OCDE STI).

Malgré une hausse de la part des dépenses réalisées par les entreprises françaises, leur contribution reste en deçà de celle des pays membres de l'OCDE dont l'intensité de recherche est la plus élevée. En 2017, l'ensemble des dépenses nationales étaient assurées par 56,1% des entreprises, soit une contribution inférieure respectivement de 7,5 et 22,2 points de pourcentage à celle des Etats-Unis et du Japon. De plus, les grandes entreprises réalisent 60% des dépenses contre 15% pour l'ensemble des petites et moyennes entreprises (PME), mettant en évidence l'hétérogénéité selon la taille des entreprises.
L'économie de la connaissance et de l'innovation a profondément modifié l'importance des investissements immatériels dans la création de savoir (Corrado et al., 2013). Ainsi, de récentes contributions ont formalisé et étendu le concept d'investissement dans les comptes nationaux en incorporant des dépenses stratégiques dans la croissance de long-terme des entreprises individuelles, telle que les bases de données numérisées, la R&D, le design, le

est d'inciter les entreprises à innover davantage. Depuis son introduction en 1983, le dispositif a connu de multiples réformes. Depuis la dernière réforme de 2008, il est calculé en fonction du volume des dépenses engagées. Pour une évaluation récente de l'impact de la réforme du CIR intervenue en 2008 sur la R&D et sur les brevets voir Bozio et al. (2014). Voir également Lopez and Mairesse (2018) pour une évaluation du CIR sur le coût d'usage de capital et, ainsi, sur l'intensité de R&D, la probabilité d'innover et la productivité des entreprises.

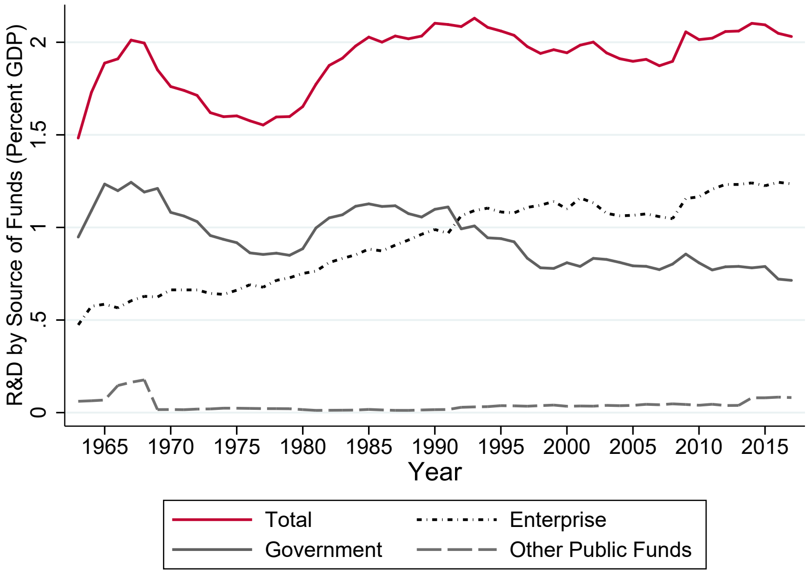


Figure 2 – Recherche et Développement en pourcentage du PIB en France, par source de financement 1963-2017.

Notes : Cette figure montre le total des dépenses de recherche et développement en pourcentage du PIB en France sur la période 1963 à 2017 par source de financement répartie entre les entreprises, le gouvernement et d'autres fonds publics tels que l'enseignement supérieur et le secteur privé à but non lucratif.
Source : Indicateurs de la science et de la technologie, séries statistiques de base, 1963-1979 / 80 (OCDE, 2015) et Collecte commune OCDE-Eurostat sur les ressources consacrées à la R&D (2020).

capital de marque, les formations propres aux entreprises et l'efficacité organisationnelle (Corrado et al., 2005)[9]. Les auteurs suggèrent que les investissements en capital immatériel sont une composante clé qui permet à l'Union Européenne de rattraper son retard de croissance sur les Etats-Unis. En effet, ils estiment que les investissements en capital immatériel représentent 7,2% du PIB au sein de l'Union Européenne (à 14 membres)[10], et 8,8% aux Etats-Unis sur la période 2000-2013. Concernant la France, la différence notable avec les Etats-Unis est la contribution relativement plus faible du capital immatériel (0,4 contre 0,6%) à la croissance de la productivité du travail. Dans l'ensemble, Corrado et al. (2016) suggèrent que les politiques favorisant l'innovation et l'environnement de marché devraient envisager l'investissement dans le capital immatériel au-delà de la R&D.

Au regard des différences statistiques concernant l'effort d'innovation et de la contribu-

[9] L'approche méthodologique de Corrado et al. (2005) a consisté à incorporer dans la mesure de l'investissement des dépenses d'actifs immatériels réalisées par les entreprises afin d'accroitre leur capacité de production future. Pour davantage de détails sur la méthodologie employée, voir Corrado et al. (2005) et Corrado et al. (2013).

[10] L'Union Européenne à 14 membres considérée par Corrado et al. (2016) comprend : l'Allemagne, l'Autriche, la Belgique, le Danemark, la Finlande, la France, la Grèce, l'Irlande, l'Italie, les Pays-Bas, le Portugal, l'Espagne, la Suède et le Royaume-Uni.

tion des entreprises à cet effort, l'analyse du comportement des entreprises et des raisons pour lesquelles une entreprise innove ou non apparaît essentielle. Quels sont les obstacles et les incitations à l'innovation, quels facteurs favorisent l'intensité technologique ? Dans ce travail doctoral, nous adoptons une approche empirique pour contribuer à la littérature de l'économie de l'innovation.

1.3 Innovation, Productivité, et Croissance

Depuis Schumpeter, les économistes soutiennent que l'innovation technologique est un moteur clé de la croissance économique[11]. L'intégration du progrès technique dans un cadre d'analyse structuré comme source de croissance à court-terme a été formalisée dans la littérature néo-classique par le modèle de Solow (1956)-Swan (1956). Une implication majeure du modèle néo-classique est que le progrès technologique est exprimé comme un stock qui s'accumule au cours du temps, mais est modélisé comme étant exogène. Par conséquent, il est modélisé en dehors de la fonction de production et évolue à un taux constant[12]. Cependant, la limite de ce modèle est qu'il ne permet pas d'évaluer l'impact des politiques publiques sur la croissance.

A partir des années 1980, les travaux de Romer (1986) ont formalisé les théories de la croissance endogène de long-terme, dans laquelle le progrès technique résulte d'une décision d'investissement par les agents économiques. Plus précisément, Romer (1986) introduit des externalités qui conduisent à des rendements croissants dans la fonction de production. La croissance de long-terme résulte donc d'une combinaison de l'accumulation de capital et des externalités [13].

Alors que les précédents modèles considéraient les connaissances comme un bien homogène, de nouvelles contributions les ont modélisées comme un facteur hétérogène. Dans les modèles de croissance basés sur l'innovation, les nouvelles technologies résultent d'une décision stratégique, de la part d'entreprises ou d'inventeurs et de l'investissement en R&D (ou connaissance). Le modèle de Romer (1990) considère les nouvelles technologies introduite sur marché par une nouvelle variété de produit, alors que les théories de la croissance Schumpétérienne (par exemple, Aghion and Howitt 1992, Aghion et al. 2001, Grossman and Helpman 1991) considèrent l'innovation comme l'introduction d'un

[11] Voir par exemple Smith (1776) et Schumpeter (1911)

[12] Le modèle prédit également une convergence du capital par tête par le biais d'un mécanisme de diffusion du progrès technique des économies avancées vers les pays en développement (c.-à-d., processus de rattrapage). Voir par exemple Barro and Sala-i Martin (1992) et Barro and Sala-i Martin (2003).

[13] Voir également le modèle développé par Lucas Jr (1988), dans lequel des retombées sont introduites grâce aux externalités engendrées par le capital humain.

produit ou d'une technologie rendant obsolète les précédentes. Ce phénomène est décrit comme un processus de *"création-destruction"*[14]. L'ensemble des caractéristiques des modèles de croissance endogène basés sur l'innovation dépendent donc des incitations à investir dans le progrès technologique, ayant par conséquent des implications en termes de politique publique. En effet, ces modèles permettent aux décideurs publics de jouer un rôle central dans la croissance à long-terme grâce à des politiques ayant un impact sur un ensemble de facteurs essentiels à la croissance, tels que l'amélioration du fonctionnement des marchés, l'investissement dans les infrastructures et la formation du capital humain.

Néanmoins, les connaissances et l'innovation (qu'elle soit radicale ou incrémentale) sont des biens qui se distinguent des biens courants (Nelson, 1959; Arrow, 1962b). Les externalités qui en résultent dans les économies de marchés sont susceptibles de décourager l'effort de recherche et d'innovation privé, mais également de réduire la productivité et de la croissance de long-terme (Bloom et al., 2019).

La présente thèse évalue différents aspects des incitations à innover à la fois au niveau macroéconomique et microéconomique. Considérés comme un ensemble, les trois chapitres de la thèse explorent différentes dimensions de la réponse des pays et des entreprises à différents instruments, directs et indirects, pour répondre aux défaillances de marché identifiées par la littérature.

2 Pourquoi Stimuler l'Effort d'Innovation ?

2.1 Défaillances de Marché : Enseignement de la Littérature

Plusieurs contributions majeures de la littérature sur l'économie de l'innovation ont abordé les facteurs internes ou externes ayant des incidences directes sur la capacité à mener des activités innovantes. L'analyse des facteurs entravant l'effort d'innovation ou encore les déterminants économiques constitue un domaine de recherche largement exploré, mais qui n'est pas pour autant épuisé. La littérature met en lumière que la capacité d'innovation au niveau de l'entreprise dépend d'un ensemble de facteurs, dont l'environnement général dans lequel les acteurs opèrent. Cet ensemble de facteurs susceptibles de contribuer à l'innovation comprend la disponibilité de ressources humaines (main d'œuvre qualifiée, chercheurs), la présence d'institutions financières dont les apporteurs de capitaux aux jeunes entreprises innovantes, un secteur de l'enseignement

[14] Voir également les contributions théoriques sur les modèles d'innovation et de dynamique des entreprises en équilibre général (Klette and Kortum, 2004; Lentz and Mortensen, 2008, 2016; Garcia-Macia et al., 2019; Akcigit and Ates, 2019).

supérieur puissant (formation), un système de protection de la propriété intellectuelle, un système juridique, au droit des faillites, un fonctionnement efficace du marché du travail, un marché intérieur dynamique et la présence de concurrents (Teece, 2010). La figure 3 propose un schéma synthétique des principaux éléments clés qui relient la croissance de la productivité-innovation et les facteurs influençant l'effort d'entreprendre des activités innovantes. Pourtant, la décision stratégique de s'engager dans des activités innovantes, la production de savoir et son succès, sont des phénomènes complexes à analyser tant théoriquement qu'empiriquement du fait des interactions entre l'ensemble des facteurs (mais également des acteurs) ainsi que les problèmes de sélection et biais de variable omises[15].

Plusieurs défaillances de marchés ont été mises en avant par la littérature afin d'expliquer l'insuffisance des incitations à innover des entreprises. Les spécificités inhérentes des investissements en R&D, en connaissance et en capital intangible sont susceptibles de limiter l'effort d'innovation privé. En effet, la principale caractéristique des investissements en capital intangible consacrés au processus d'invention et d'innovation est la production de connaissance, qui a la propriété d'un bien public, non-rival (Arrow, 1962b; Nelson, 1959). Par conséquent, l'utilisation d'une connaissance qui a été produite par une entreprise n'empêche pas son utilisation par une autre entreprise, concurrente ou non. Dans la mesure où la production de nouvelles connaissances ne peut être gardée secrète, les rendements de l'investissement ne peuvent pas être appropriés par l'entreprise dans sa globalité, accentuant le risque de sous-investissement dans l'économie de la connaissance et de l'innovation par des acteurs privés. L'existence de défaillances de marchés est ainsi un argument utilisé par les décideurs publics afin de justifier l'intervention publique pour promouvoir l'innovation et encourager la croissance économique (Hall et al., 2010; Bloom et al., 2019).

Ce travail doctoral s'intéresse aux défaillances de marchés associées aux problèmes d'appropriation incomplète des rendements de l'investissement et aux contraintes de financement de la R&D et de l'innovation. Il ne vise pas à aborder l'ensemble des facteurs susceptibles d'influencer la décision d'innover ou encore les facteurs contraignant l'effort des entreprises synthétisés dans la figure 3. Par conséquent, ces éléments ne seront pas analysés ici.

[15]Voir également la littérature sur les systèmes d'innovation, national, régional, ou spécifique à une technologie dans lesquelles la production de savoir/innovation est un processus interactif (Edquist, 1997; Lundvall, 2010; Nelson, 1993).

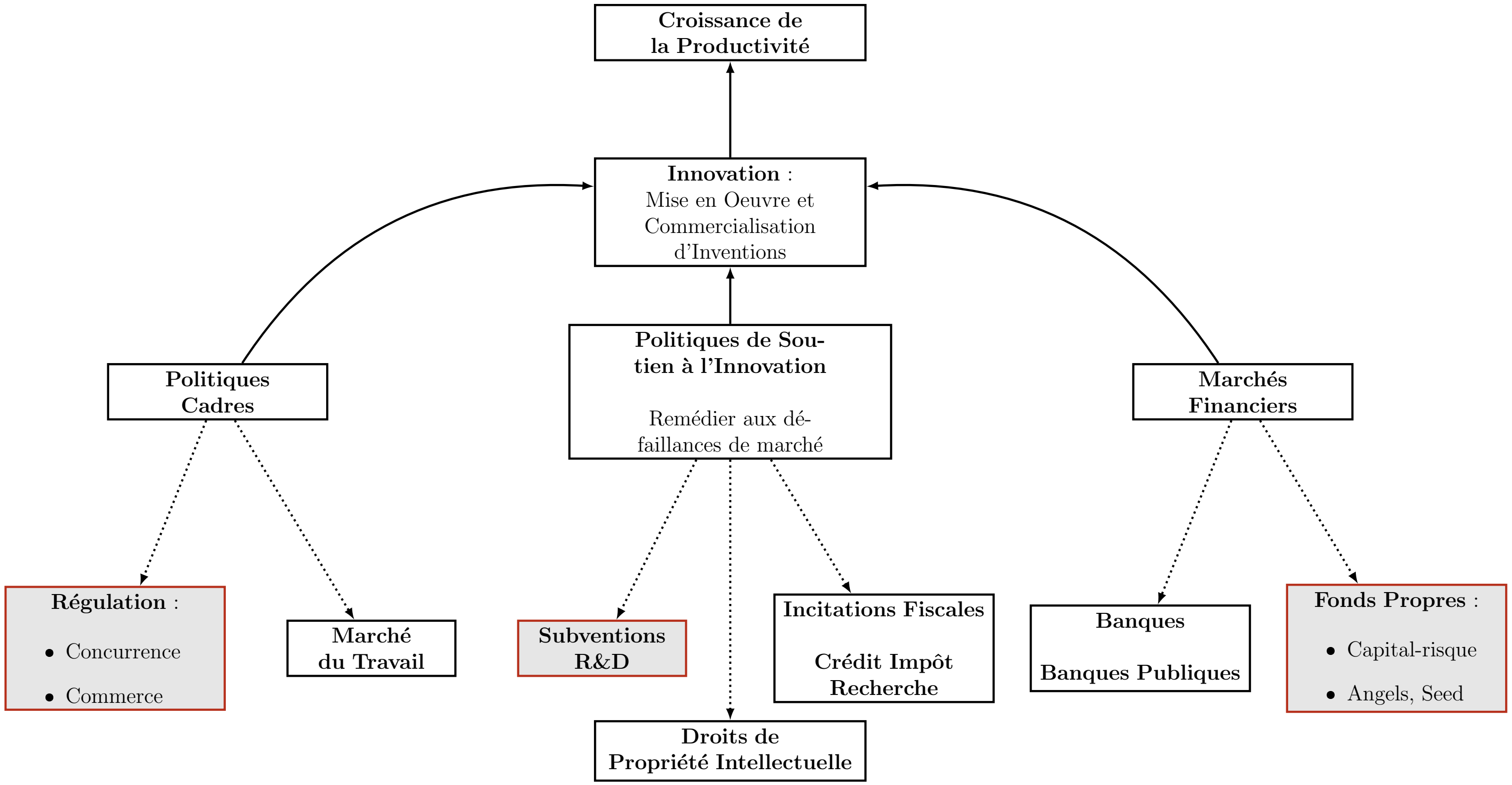


Figure 3 – Schéma Récapitulatif Productivité-Innovation et Facteurs Favorisant l'Effort d'Innovation.

Notes : Cette figure propose un schéma non exhaustif des politiques dédiées à stimuler l'effort de R&D des entreprises ainsi que l'environnement (programmes cadres et développement du secteur financier) auxquel les entreprises sont confrontées.

Retombées de la Connaissance (Knowledge Spillovers)

Selon la théorie économique, dans le cas d'investissement en R&D et en actifs intangibles, en concurrence parfaite, le bien-être social ne peut pas être maximisé du fait des problèmes inhérents aux activités innovantes qui sont fortement affectées par la non-appropriabilité et l'incertitude qui empêchent les entreprises d'internaliser l'ensemble des bénéfices des investissements (Griliches, 1958). Ainsi, si une entreprise développe un produit ou un procédé innovant[16], la connaissance peut se diffuser vers d'autres entreprises qui ont la possibilité de tirer des enseignements des précédentes recherches ou imiter une invention, sans assumer l'ensemble des coûts associés à la R&D. Par exemple, Mansfield et al. (1981) suggèrent qu'imiter une invention pourrait avoir un coût jusqu'à cinquante à soixante-quinze pour cent inférieur au coût de la R&D nécessaire au développement de l'invention originelle. La contribution de Griliches (1958), à partir d'une étude de cas sur le coût de la recherche sur le maïs hybride, montre que le rendement social annuel des investissements publics et privés est égal à 700 %, par dollar moyen investi dans la recherche. Des contributions plus récentes montrent, en s'appuyant sur des données de panel d'entreprises américaines, que les retombées sociales de la R&D sont deux à trois fois supérieures aux retombées privées (Bloom et al., 2013).

Ce phénomène d'externalités positives qui réduisent les incitations des entreprises à investir en R&D n'est cependant pas le seul mécanisme des retombées de connaissances. Ces dernières favorisent des complémentarités dans les efforts de R&D des entreprises (Cohen and Levinthal, 1989). Les nouvelles connaissances (R&D) sont un facteur déterminant de l'apprentissage et permettent d'accroitre la capacité des entreprises à *"absorber"* (absorptive capacity) et assimiler de nouveaux savoirs[17].

Ces externalités crées par le processus d'innovation sont citées régulièrement dans la littérature afin de justifier l'utilisation d'instruments publics (Bloom et al., 2013). Afin d'assurer une allocation optimale des ressources vers l'innovation, la grande majorité des pays industrialisés ont mis en place des politiques publiques afin de stimuler l'activité de R&D privée[18]. Les interventions publiques les plus fréquemment mises en

[16] Une innovation est la mise en œuvre (implémentation) d'un produit (bien ou service) ou d'un procédé (de production) nouveau ou sensiblement amélioré, d'une nouvelle méthode de commercialisation ou d'une nouvelle méthode organisationnelle dans les pratiques d'une entreprise, l'organisation du lieu de travail ou les relations extérieures (OCDE, Manuel d'Oslo, p. 54).

[17] La notion de capacité d'absorption est un facteur déterminant de la littérature sur la diffusion des technologies (Keller, 2004; Bloom et al., 2013), la productivité des entreprises (Jaffe, 1986; Cockburn and Henderson, 1998), la coopération entre entreprises (Branstetter and Sakakibara, 2002), et la croissance économique et le rattrapage (Griffith et al., 2003).

[18] En 2019, 30 pays membres de l'OCDE accordaient une incitation fiscale aux dépenses de R&D privé.

œuvre en présence d'externalités sont les droits de propriété intellectuelle (par exemple, brevet, trademark), des incitations indirectes par le biais de réductions fiscales (Guceri and Liu, 2019) et l'octroi de subventions directes aux activités de R&D (Howell, 2017). Le deuxième chapitre de la thèse propose d'examiner cet instrument de politique publique.

Contrainte de Financement

Une autre défaillance de marché avancée par la littérature conduit elle aussi au sous-investissement des entreprises en R&D et en actifs intangibles. Il s'agit des contraintes de financement auxquelles sont confrontées les entreprises innovantes[19]. L'argument principal avancé est qu'il existe un écart entre le taux de rendement privé de l'investissement et le coût du capital lorsque l'entreprise ou l'entrepreneur finance son investissement par des sources de capitaux externes (Hall et al., 2010). La sévérité des contraintes de financement engendre donc le risque que certaines opportunités d'investissements rentables (NPV positive) soient abandonnées si les fonds internes sont insuffisants, ajoutant une défaillance de marché à celle évoquée auparavant.

Les spécificités des investissements en R&D et innovants renforcent la difficulté de les financer par rapport aux investissements traditionnels (Kerr and Nanda, 2015). Plusieurs études examinent la sensibilité des investissements en R&D aux flux de trésorerie. Par exemple, Hall et al. (2016) rendent compte d'une relation négative entre les investissements en innovation et les contraintes de financement des entreprises européennes. De même, Cincera et al. (2016) suggèrent que les innovateurs européens sont plus limités financièrement que les innovateurs américains et cette contrainte est renforcée pour les plus jeunes innovateurs de premier plan. Premièrement, le résultat des investissements en R&D est un actif intangible, *"tacit"* et propre aux projets d'une entreprise[20]. Le capital intangible est un actif spécifique, au sens de Williamson (1988) souvent difficile à redéployer en cas d'échec du projet pour lequel il a été constitué, et ne peut être utilisé comme garantie pour recourir à un prêt bancaire. Deuxièmement, les projets innovants sont risqués, au sens où le résultat (succès) est fortement incertain, renforçant le problème d'asymétrie d'information, d'anti-sélection et d'aléa-moral entre l'entreprise et des investisseurs externes. Selon le théorème de Modigliani and Miller (1958), et

[19] Par exemple, d'après l'enquête communautaire sur l'innovation menée en 2016 (CIS2016), 7,8% des entreprises françaises innovantes ont rencontré des contraintes de financements externes, crédit ou capital privé inclus, entre 2014-2016. Outre ces manques de financements externes, l'enquête a révélé que 14,3% des entreprises ont également souffert d'un manque de ressources internes afin de financer leurs activités d'innovation.

[20] Hall et al. (2010) suggèrent que 50% des dépenses de R&D privée correspondent aux salaires et traitements des ingénieurs et scientifiques de l'entreprise, soit son capital humain.

sous l'hypothèse de marchés financiers parfaits, les niveaux optimaux d'investissements sont indépendants de la structure du capital d'une entreprise. Ainsi, les financements interne et externe sont parfaitement substituables. Cependant, les problèmes d'opacité informationnelle entre une entreprise (ou un porteur de projet) et des investisseurs potentiels accroît le coût du financement externe par rapport au financement interne[21]. Enfin, les frictions informationnelles peuvent entrainer des problèmes de sélection adverse (ou anti-sélection), portant sur la qualité des projets (Myers and Majluf, 1984). Le problème de sélection adverse résulte de la difficulté intrinsèque à évaluer le potentiel de succès d'un projet innovant par des investisseurs non spécialisés. Pour réduire le biais informationnel, une entreprise a la possibilité de divulguer des informations sur le contenu innovant de leur projet et ainsi envoyer un signal sur la qualité du projet au marché. Cependant, Hall (2002) suggère que de révéler de l'information est peu efficace, en raison du risque d'imitation par des concurrents potentiels.

Enfin, la littérature suggère que les imperfections des marchés des capitaux qui entravent la capacité des entreprises à accéder aux financements externes, sont davantage prononcées pour les petites ou jeunes entreprises[22]. Cet argument justifie souvent une politique de soutien dédiée à ces entreprises (incitations fiscales, subventions), mais aussi le développement de marchés financiers spécifiques aux investisseurs en phase de démarrage ou bien des mécanismes non-financiers afin d'identifier de nouveaux projets à fort potentiel de croissance (Howell, 2019; Bloom et al., 2019). Les deux derniers chapitres de la thèse proposent d'examiner sous deux angles différents l'impact des contraintes de financement, en mettant en avant deux mécanismes distincts.

2.2 L'Ecosystème de l'Innovation : Incitations à Innover

Les défaillances de marché décrites précédemment justifient l'existence d'incitations à la production de connaissances et d'innovation issues du secteur privé. Les politiques publiques dédiées à l'innovation ou tout autre mécanisme affectant l'environnement dans lequel évoluent les entreprises sont susceptibles d'influencer l'effort d'innovation privé et, par conséquent, la croissance de long-terme (Aghion and Howitt, 1992; Grossman and

[21]Le problème d'asymétries d'information entre investisseurs et inventeur se réfère au *"lemon's market"* (Akerlof, 1970), selon lequel un porteur de projet a un avantage informationnel sur la nature du projet mené, de ses caractéristiques, et de la probabilité de succès par rapport à de potentiels apporteurs de capitaux externes à la structure de l'entreprise. Enfin, l'ensemble de ces caractéristiques impliquent une difficulté supplémentaire pour les investisseurs potentiels à distinguer les projets à fort potentiel relativement aux projets dont la probabilité d'échec est élevée, augmentant le coût du financement externe (Leland and Pyle, 1977).

[22]Voir Hall et al. (2010) pour une revue de la littérature récente sur les contraintes de financement accrue pour les jeunes et/ou petites entreprises innovantes.

Helpman, 1991).
Dans cette thèse, nous ciblons notre analyse sur les défaillances de marché mentionnées par la littérature, en particulier les difficultés d'accès aux financements externes des entreprises innovantes. Nous envisageons la question des incitations à la R&D et à l'innovation à travers trois mécanismes dont l'objectif est de stimuler l'effort privé de recherche et la réduction des asymétries d'information.

Régulation de la concurrence nationale et étrangère

L'impact de la concurrence sur l'effort d'innovation est théoriquement ambigu. D'une part, Schumpeter (1934) a soutenu qu'un degré élevé de concurrence tend à réduire les incitations à innover, en réduisant les profits de monopole. Dans la mesure où le profit qu'une entreprise retire de son effort est issu d'un pouvoir de marché, une concurrence élevée peut impliquer une réduction des bénéfices futurs, limitant par conséquent les fonds internes disponibles pour investir en capital intangible et, donc, amplifier les problèmes d'accès aux capitaux externes (Bloom et al., 2019).

En revanche, Arrow (1962a) montre qu'en situation de monopole pur, sans exposition à la concurrence technologique, existante et nouvelle, une entreprise sera moins incitée à innover[23]. En effet, un une entreprise en situation de monopole peut innover et augmenter ses bénéfices, mais perd le flux de profit de son ancienne technologie (*"l'effet de remplacement"*). L'impact de la concurrence sur l'innovation reste donc une question ouverte et d'actualité.

De récentes contributions ont documenté plusieurs faits stylisés sur le déclin du dynamisme des entreprises aux Etats-Unis et dans d'autres pays développés, dont une augmentation de la concentration du marché (par exemple, Dorn et al. 2017, Autor et al. 2016, et Akcigit and Ates 2019), des markups (par exemple, Barkai 2016 et Calligaris et al. 2018), ainsi qu'une réduction de la part des jeunes entreprises dans l'activité économique (par exemple, Decker et al. 2016). Pourtant, les travaux empiriques suggèrent que la concurrence tend à augmenter l'innovation. Une première partie de la littérature fait valoir l'importance des réformes pro-concurrentielles sur le marché des produits, augmentant le degré de concurrence entre entreprises afin d'accroitre la dynamique d'entrée de nouveaux acteurs (Andrews and Criscuolo, 2013). Ainsi, ces

[23] Cependant, les prédictions du modèle d'Arrow (1962a) ne s'appliquent pas directement aux nouveaux produits, mais aux procédés (Gilbert, 2006). Contrairement aux produits, un nouveau procédé domine technologiquement les précédents, par conséquent, l'ancienne technologie n'a pas de lien avec le profit qu'une entreprise en situation de monopole peut espérer avec le nouveau procédé.

réformes influencent positivement l'investissement en R&D et en innovation (Ciriaci et al., 2016; Canton et al., 2014). Une littérature plus récente s'est, quant à elle, concentrée sur l'effet de l'ouverture commerciale, de son impact sur la concurrence et la diffusion des connaissances[24]. En utilisant notamment l'entrée de la Chine dans l'Organisation Mondiale du Commerce (OMC) en 2001, Bloom et al. (2016) suggèrent que pour l'Europe, une augmentation de la concurrence par le biais des importations provenant de Chine est associée à une augmentation des brevets (EPO), des investissements en technologie de l'information et une croissance de la productivité (TFP) conditionnellement à la survie des entreprises. Néanmoins, ces résultats diffèrent sensiblement des preuves empiriques concernant les entreprises basés en Amérique du Nord qui suggèrent un effet négatif sur les brevets (Autor et al., 2016), une probabilité plus faible d'investir dans les innovations de processus (Bena and Simintzi, 2016) et une réallocation de la R&D vers les entreprises les plus productives et rentables (Xu and Gong, 2017). Enfin, Aghion et al. (2005) réconcilie l'argument de Schumpeter (1934) et Arrow (1962a), dans lequel l'impact de la concurrence sur l'innovation est représenté sous la forme d'un U inversé.

Le premier chapitre de la thèse propose d'apporter un nouvel éclairage sur la relation entre la régulation de la concurrence nationale et étrangère d'une part et l'intensité d'innovation d'autre part, en se focalisant sur une approche empirique originale afin d'analyser l'interaction entre les deux types de régulation.

Subventions R&D

Le recours à des interventions publiques, directes ou indirectes afin de stimuler l'investissement en R&D privée est une politique de soutien aux entreprises régulièrement mise en place par les gouvernements. L'objectif de ces interventions publiques est de répondre au sous-investissement en R&D du aux défaillances de marché précédemment décrites (voir Section 2.1) à savoir la présence de retombées de connaissance (Nelson, 1959; Arrow, 1962b) et des contraintes financières (Hall et al., 2010). Ces défaillances de marché affectent en particulier les jeunes et petites entreprises innovantes. Parmi les instruments les plus couramment utilisés pour surmonter ces défaillances, les subventions à la R&D représentent la forme la plus directe de soutien à l'effort d'innovation privé (Howell, 2017). Contrairement aux mesures indirectes de politiques telles que les incitations fiscales à la R&D, les subventions directes ont l'avantage de mieux cibler les

[24] L'ouverture commerciale peut intensifier l'effort d'innovation des entreprises en leur permettant, à la fois d'accéder aux connaissances étrangères (Coe and Helpman, 1995), accroître la taille du marché (Grossman and Helpman, 1991), ou par le biais d'effets de réallocation des ressources favoriser les gains de productivité (Melitz, 2003).

dépenses de R&D à même de créer des retombées de connaissances. En effet, une crainte des décideurs politiques est que les entreprises rebaptisent leurs dépenses d'investissement ordinaires en dépenses de R&D afin de bénéficier d'une déduction fiscale plus importante (Guceri and Liu, 2019; Chen et al., 2018). Le soutien public à l'innovation a entrainé une vaste série d'études empiriques qui ont évalué l'effet des subventions sur les dépenses de R&D, l'investissement, et le capital humain, mais fournissent des conclusions mitigées quant à leur efficacité (David et al., 2000; Zúñiga-Vicente et al., 2014).

Les conclusions de la littérature peuvent être classées comme révélant un effet d'additionalité (par exemple, Einiö 2014), d'éviction (par exemple, Wallsten 2000, Lach 2002, et Marino et al. 2016), ou sans effet sur l'effort de R&D privé (par exemple, Hünermund and Czarnitzki 2019 et Görg and Strobl 2007). Cependant, de récentes contributions qui utilisent des données au niveau de l'entreprise (ou projet) et qui exploitent comme source de variation exogène le seuil dans le processus d'attribution des subventions pour isoler l'effet causal du traitement, mettent en évidence un effet bénéfique des politiques publiques[25]. Par exemple, Bronzini and Piselli (2016) examinent un programme mis en œuvre dans le nord de l'Italie et trouvent un impact significatif sur le nombre de brevets déposés et la probabilité de soumission d'une demande pour les entreprises bénéficiaires. De même, Howell (2017) estime que l'octroi d'une subvention au stade de *"proof-of-concept"* a des effets positifs sur le nombre de brevets pondérés par les citations, la survie des entreprises et la probabilité de recevoir un financement par capital-risque. L'ensemble de ces contributions suggère que les programmes de subventions à la R&D sont particulièrement bénéfiques pour les entreprises susceptibles d'être contraintes financièrement, à savoir les petites et jeunes entreprises (Bronzini and Iachini, 2014; Howell, 2017; Söderblom et al., 2015). D'un point de vue politique, l'hétérogénéité au sein d'un même programme de subvention à la R&D suggère l'importance de cibler la population d'entreprise pour laquelle l'incitation sera la plus élevée.

Le deuxième chapitre de la thèse contribue à la littérature sur l'évaluation de programmes de subventions à la R&D privée en proposant de nouvelles preuves empiriques à partir d'un programme européen et en abordant un certains nombres de questions dont les résultats sont ambigus.

[25] L'ensemble de cette littérature tire parti d'un accès à des données administratives portant sur l'ensemble des entreprises qui sollicitent mais n'obtiennent pas forcément la subvention pour laquelle elles ont candidaté. Ces données permettent d'avoir accès aux groupes de comparaisons naturels (groupe de contrôle) et, ainsi, de garantir que le groupe traité et de contrôle fassent parti du même pool de candidats (Zhao and Ziedonis, 2020). Cette stratégie d'identification à l'avantage de surmonter le biais de sélection et d'endogénéité, mais l'effet estimé est localisé autour d'un seuil et donc limité en termes de validité externe.

Environnement entrepreneurial

L'entrepreneuriat a longtemps été présenté comme un moteur clé de l'élévation du niveau de vie et de l'innovation (création-destruction) (Smith, 1776; Schumpeter, 1942). Cependant, les asymétries d'information et le risque liés aux projets innovants, sont exacerbés pour les entrepreneurs et les entreprises en phase de création (Gompers and Lerner, 2001).

Les entreprises en phase de démarrage ne disposent pas de fonds internes suffisants pour financer leurs investissements et font face à un manque de garanties pour des investisseurs traditionnels, ce qui restreint leur croissance et profits futurs. Ces spécificités conduisent les jeunes entreprises innovantes à se financer par fonds propres auprès d'investisseurs spécialisés, tels que les business-angels et sociétés de capital-risque. Ces investisseurs ont un rôle ex-ante de sélection, d'investisseurs et une participation active dans le suivi et le conseil de leur portefeuille d'entreprises (Kaplan and Stromberg, 2001; Kaplan and Lerner, 2010). Les mesures prises par ces investisseurs spécialisés permettent de soutenir des entreprises à fort potentiel de croissance et de promouvoir l'innovation (Hellmann and Puri, 2000; Gornall and Strebulaev, 2015; Bernstein et al., 2016). Ceci est conforme avec l'ensemble des initiatives prises par les gouvernements visant à stimuler l'environnement entrepreneurial et l'investissement par capital-risque (Lerner, 2013).

Cependant, ces dernières années, des chocs technologiques ont permis de réduire sensiblement le coût de la création d'une entreprise innovante (en particulier dans le secteur digital et le service aux entreprises) et l'expérimentation entrepreneuriale (Ewens et al., 2018). Cela a entrainé une augmentation du nombre d'entreprises en phase de démarrage et de nouvelles opportunités d'investissements pour les investisseurs qui n'auraient pas bénéficié de soutien financier auparavant. Cette récente tendance a pour conséquence d'accroitre l'incertitude quant à la qualité des projets entrepreneuriaux, intensifiant les traditionnels problèmes d'asymétries d'information entre les entrepreneurs et les investisseurs potentiels qui sélectionnent les entreprises à un stade précoce[26]. Ainsi, de nouveaux intermédiaires ont émergé afin de sélectionner des projets, faciliter l'accès à de nouvelle source d'information, réduire l'incertitude autour de la qualité de succès d'un projet innovant et par conséquent, sur la trajectoire de l'innovation (Cohen and

[26] Ewens et al. (2018) indiquent que les sociétés de capital-risque basées aux Etats-Unis ont, à la suite des récents chocs technologiques, profondément modifiés leur stratégie d'investissement. Elles adoptent à présent une approche de *"spray and pay"*, qui a pour conséquence une réduction des montants investis ainsi qu'un suivi limité, au bénéfice d'un plus grand nombre de projets supportés.

Hochberg, 2014; Gonzalez-Uribe and Reyes, 2019; Gonzalez-Uribe and Leatherbee, 2018).

Néanmoins, les travaux empiriques sur la capacité de ces nouveaux intermédiaires à réduire les asymétries d'informations et de leur incidence sur les futures performances des entreprises restent limités. Howell (2019) utilise des données portant sur les nouveaux concours d'entreprises aux Etats-Unis sur la période 2007-2015 et compare les entrepreneurs qui ont remporté une session et ceux qui ont de peu échoué en étant classé au-delà d'un certain seuil (note attribuée aux projets). Elle montre que remporter une session influence positivement la probabilité que ces entrepreneurs lèvent ultérieurement des fonds auprès d'investisseurs, qui ont alors 35% de chance d'être financés de plus que la moyenne de ceux qui ont échoués. Une explication de cet effet est que les classements des juges prédisent fortement le succès et certifient la qualité en envoyant un signal aux investisseurs en démarrage, réduisant ainsi les frictions liées à l'information[27].

D'autres intermédiaires demeurent négligés par la littérature. Il s'agit des incubateurs et des accélérateurs qui fournissent aux entreprises en phase de création des programmes à durée déterminée, un espace d'hébergement, des formations à l'entrepreneuriat et un financement (Gonzalez-Uribe and Leatherbee, 2018). Les preuves empiriques varient selon le programme évalué et la stratégie d'identification mise en œuvre. Cependant, l'ensemble des analyses mettent en avant que ces programmes semblent significativement influencer la performance des entreprises par le biais du mentorat, des interactions avec des pairs, et leur permet de résoudre les problèmes d'incertitude quant au potentiel d'un projet (Gonzalez-Uribe and Leatherbee, 2018; Yu, 2020; Leatherbee and Katila, 2017).

Un système de financement alternatif qui repose sur une évaluation d'une communauté non experte pour soutenir l'entreprise via des plateformes de financement participatif émerge depuis peu. Le financement participatif offre un système de financement entrepreneurial différent de celui des investisseurs (VC) traditionnels. En effet, la foule peut avoir la possibilité de divulguer des informations sur l'entreprise et de signaler la qualité du projet à des prospects. Mollick (2013) et Mollick and Nanda (2016) examinent si la foule et les experts divergent dans leur prise de décision pour financer des projets entrepreneuriaux. Ils trouvent une concordance entre la décision de financement de la foule et des experts et montrent que la qualité du projet est évaluée de manière similaire. Ainsi, ces résultats suggèrent que ce mode de financement peut réduire les contraintes de

[27]Dans une étude connexe, Howell (2018) examine si les perdants au cours de la phase de compétition sont sensibles aux commentaires négatifs des juges et comment les fondateurs poursuivent leur entreprise. Par exemple, recevoir une rétroaction négative augmente la probabilité de poursuite de 13% (par rapport à la moyenne). De plus, cet effet est hétérogène en fonction des caractéristiques du fondateur.

financement des entreprises en phase de démarrage, en particulier sur la validation de la *"traction"* auprès des investisseurs spécialisés.

Le dernier chapitre de la thèse contribue à cette littérature naissante sur les nouveaux intermédiaires dédiés aux entreprises en phase de démarrage, en proposant une évaluation des projets entrepreneuriaux lancés sur une plateforme de notation participative et en examinant dans quelle mesure le score attribué signale la qualité de l'entreprise aux investisseurs potentiels.

3 Contributions Proposées par la Thèse

Cette thèse est organisée en trois chapitres distincts, chacun d'entre eux abordant une question de recherche spécifique. Le questionnement abordé dans le premier chapitre reposera sur une analyse au niveau macroéconomique. Le deuxième chapitre de la thèse porte sur une politique européenne et s'appuiera sur des données d'entreprises pour un ensemble de pays européens, tandis que le dernier chapitre se concentrera sur un questionnement au niveau microéconomique et mobilisera des données individuelles d'entreprises implantées en France.

Le premier chapitre de la thèse, intitulé *"The Impact of Market Regulation on Innovation : An Analysis of Direct and Indirect Effects"* propose une réévaluation de la relation entre innovation et concurrence. Malgré une littérature théorique et empirique abondante, la relation entre l'innovation et la concurrence reste une question de recherche ouverte. En utilisant des données pays-années sur l'intensité d'innovation d'un ensemble de pays membre de l'OCDE, complétées par des informations sur les règles juridiques capturant les réglementations de marché, nous analysons l'impact de la concurrence sur l'innovation de 1995 à 2015, en faisant la distinction entre les politiques de concurrence nationales et étrangères. Les contributions de ce chapitre sont avant tout empiriques, et leur objectif n'est pas uniquement d'évaluer l'efficacité des politiques de la règlementation de la concurrence, mais aussi de caractériser les interactions entre la réglementation de la concurrence intérieure et extérieure et de mieux comprendre leur effet sur l'intensité d'innovation.
Premièrement, la concurrence produit-marché accroît l'innovation. Les pays qui réduisent la réglementation intérieure augmentent l'intensité de la R&D et déposent davantage de brevets. En revanche, une réglementation qui accroît l'ouverture commerciale augmente considérablement le nombre de brevets déposés mais n'a en revanche aucun effet sur la R&D. Deuxièmement, lorsque nous utilisons des indicateurs de réglementation désagrégés,

nous constatons que les pays qui accroissent la dynamique des entreprises en réduisant les barrières administratives ont en moyenne des niveaux plus élevés d'investissements en R&D et de brevets, bien que l'indicateur mesurant la difficulté de démarrer une nouvelle entreprise semble avoir l'effet le plus prononcé sur l'innovation. Enfin, les pays confrontés à des barrières tarifaires moins élevées investissent en moyenne moins dans la R&D, alors que réduire les barrières non tarifaires (c'est-à-dire en augmentant la concurrence à l'importation) a un impact positif sur le nombre de brevets déposés. Enfin, compte tenu des preuves empiriques ambiguës entre l'effet de la régulation des marchés de produits et de la concurrence des importations sur l'innovation, nous utilisons une méthodologie de structure causale qui permet de découvrir des relations causales endogènes et d'ordonner les déterminants de l'innovation sans spécifier un modèle a priori. En utilisant cette stratégie d'identification, nous constatons que seule la réglementation intérieure est un déterminant causal de la R&D et des brevets.
La principale implication en termes de politique publique des résultats de ce chapitre est que la politique de la concurrence, en augmentant le niveau de concurrence entre les entreprises et en réduisant les barrières à l'entrée, peut accroître l'intensité d'innovation. Ainsi, les gouvernements qui ont pour objectif stratégique de favoriser l'intensité de l'innovation pourraient réduire la réglementation de la concurrence intérieure, accroître la pression concurrentielle exercée par les nouveaux entrants pour apporter de nouvelles idées sur le marché et défier les entreprises en place. Néanmoins, l'analyse examine l'influence directe de la politique de réglementation de la concurrence sur des indicateurs mesurant à un niveau agrégé l'innovation.

Le deuxième chapitre de la thèse, intitulé *"Innovation Performance and the Signal Effect : Evidence from a European Program"* propose l'analyse d'un programme européen d'incitation directe à l'investissement en R&D des entreprises afin de promouvoir l'effort d'innovation. Ce programme "SME Instrument", dédié aux petites et moyennes entreprises (PME) innovantes a été lancé en 2014 dans le cadre du huitième programme européen Horizon2020. Ce programme, qui consiste à subventionner la R&D selon des critères d'éligibilités est similaire dans sa structure au programme de subvention Small Business Innovation Research[28]. La littérature évaluant l'impact des subventions à la R&D ne fournit pas de conclusions catégoriques quant à leur efficacité. Ce chapitre vise donc à apporter un éclairage nouveau sur le mécanisme par lequel l'octroi d'une subvention à la R&D pourrait réduire les contraintes financières des PME bénéficiaires.
Pour ce faire, nous utilisons des données de l'agence exécutive sur les entreprises

[28] Néanmoins, les montants de subventions accordés dans le cadre du programme européen sont inférieurs. Voir Lerner (2000) et Howell (2017) pour un descriptif du programme SBIR.

bénéficiaires d'une subvention en 2014 sur dix pays européens couvrant la période 2008-2017, que nous comparons à des informations de bilan ainsi que des données sur les brevets provenant de PATSTAT. À partir de cet échantillon d'analyse, nous estimons la propension d'obtenir une subvention à la R&D en fonction de caractéristiques observables des entreprises (le pays, l'âge, le secteur technologique, les actifs corporels et incorporels et le stock de brevets) et construisons un groupe témoin à partir d'un échantillon d'entreprises innovantes sélectionnées aléatoirement. Nous confirmons que la décision de postuler n'est pas aléatoire et que les entreprises bénéficiaires diffèrent, en moyenne, de l'échantillon aléatoire d'entreprises européennes avant matching. La performance d'innovation est mesurée à partir du nombre de brevets. Premièrement, nous montrons que l'attribution de subventions *"preuve de concept"* influence positivement, à la fois la marge intensive (du nombre de brevets déposés) et extensive (la probabilité de déposer un brevet), contrairement aux subventions ciblant des projets à un stade de maturité plus avancé, pour lesquels l'effet estimé est nul. Deuxièmement, nous constatons que les jeunes entreprises innovantes (c'est-à-dire âgées de moins de 8 ans) sont plus enclines à accroître leur activité de brevetage, ce qui suggère que les subventions de R&D sont une intervention politique efficace pour réduire les frictions informationnelles. Enfin, nous mettons en avant que le mécanisme à l'origine des résultats est un effet de certification qui fournit des informations aux investisseurs sur la technologie des entreprises et la qualité de leur projet.

Enfin, le dernier chapitre intitulé *"Information Frictions and Early-stage Investors : Evidence from a Crowd-Rating Platform"* propose d'analyser la capacité de nouveaux intermédiaires, en l'occurrence une plateforme de notation par la foule, de faciliter l'accès à des informations permettant de réduire l'incertitude sur la qualité des projets. Une abondante littérature argumente de l'importance des VC et BA, pourtant cette question de recherche n'a pas été abordée, à notre connaissance par la littérature.
Pour répondre à cette question, nous utilisons un échantillon de projets récemment lancés sur une plateforme entre 2015 et 2018. Nous combinons ces informations avec des informations sur le financement des projets, leur survie, l'emploi et le nombre de visites sur leur site internet. Ce chapitre propose ainsi d'évaluer cette question sur un ensemble de données uniques et propose des indicateurs empiriques peu exploités dans la littérature, approximant la réussite d'un projet entrepreneurial. Nous résolvons les principaux problèmes liés à l'endogénéité de notre variable d'intérêt par le recours à une approche par variable instrumentale. Notre variable instrumentale est fortement prédictive des notations, mais non corrélée aux caractéristiques des projets. Les résultats obtenus sont peu concluants. En effet, nous mettons en évidence que l'évaluation par la foule n'affecte pas positivement la probabilité de lever des fonds auprès d'investisseurs spécialisés, à court

et moyen terme. De même, nous ne trouvons pas d'effet significatif sur le succès d'un projet entrepreneurial. Il existe cependant une exception à l'ensemble des résultats. Selon les caractéristiques des projets, nous trouvons des preuves suggérant que la foule peut discriminer différemment selon le stade de développement du projet. Dans leur ensemble, ces résultats suggèrent la difficulté inhérente du processus de sélection et d'identification ex-ante des jeunes entreprises innovantes à fort potentiel de croissance.

Chapter 1

The Impact of Market Regulation on Innovation: An Analyis of Direct and Indirect Effects

---

Summary of the Chapter

Theoretical effects of competition regulations on innovation are ambiguous. In this chapter, we estimate the impact of domestic and foreign competition-increasing product market reforms on R&D and patenting on 25 OECD countries over the period 1995-2015. First, we find that product market reforms increasing domestic and foreign competition enhanced innovation intensity. Second, the source of enhancing-competition regulations on innovation may not be equally important. Using graphical approach to causality, we provide evidence that domestic regulation enhancing product-market competition is the only direct cause of innovation intensity. This result has important policy implications for prioritizing reforms. The observed direct causal effect of domestic competition suggests that lessen domestic regulation could enhance innovation progress in OECD countries.

Classification

JEL Classification: O30, O31, L5, C52.

Keywords: Regulation, Innovation, OECD countries, Directed Acyclic Graph.

Acknowledgments for this chapter

I am grateful to Nadine Levratto for their continued guidance and support. For helpful comments and discussions, I thank Maryann Feldman, Jacques Mairesse, Thierry Philipponnat, Renaud Redien-Collot and conference participants at the KID 2018 Thematic School CNRS.

Contents of the Chapter

1 Introduction

There is broad consensus on the relationship between innovation and productivity growth on endogenous growth literature and policymakers (e.g., Grossman and Helpman 1991, Romer 1990, and Aghion and Howitt 1992)[1]. This broad consensus contrasts with the ambiguous evidence of the effects of competition on innovation. This chapter empirically considers the effectiveness of competition on innovation, differentiating between domestic and foreign competition. In particular, we examine how these sources of competition influence directly innovation intensity, which is relevant in prioritizing reforms.

In theory, the effect of competition-enhancing product market regulation on innovation relies on opposing arguments[2] proposed by Schumpeter (1934) and Arrow (1962b). Schumpeter (1934) argued that increasing market competition discourages innovation (i.e. "Schumpeterian effect") through lower expected R&D investment payoffs (e.g., Dasgupta and Stiglitz 1980, Dixit and Stiglitz 1977, and Romer 1990). By contrast, Arrow (1962b) argued that competition increases the incentive to innovate through an escape effect, increasing innovation rents (e.g., Gilbert and Newbery 1982 and Reinganum 1983). Alternative theoretical contributions introduce a model in which the Schumpeterian and escape effects get along with innovation intensity through an inverted U-shape (Aghion and Howitt, 1998). Thus, at the country level, competition-enhancing policies might have opposite effects on innovation intensity, according to the market structure (i.e., technology gap between firms) and initial level of competition.

In this chapter, we examine the linear impacts of the domestic and foreign product-market competition regulation on R&D intensity and patenting, how they directly or indirectly cause innovation using comprehensive data covering 25 OECD countries for the period 1995 to 2015[3]. To measure domestic and foreign product-market regulation, we use aggregate as well as sub-indicators on factors capturing regulations and bureaucratic procedures restrain entry, trade restrictions that reduce competition. These indicators are based on opinions and allow us to reduce endogeneity bias compared to the most

[1]For example, Corrado et al. (2012) estimate that knowledge capital investments contribute to 0.5 percentage points of GDP growth in European countries and 0.9 percentage points in the United States.

[2]For a review on the relationship between innovation and competition, see Gilbert (2006) and Cohen (2010)

[3]Our identification strategy assumes that the relationship between innovation intensity and competition is linear at the country level and we do not examine the inverted-U shape. A large literature provides evidence of non-linearity, see for example Aghion et al. (2005), Negassi et al. (2019), and Tingvall and Poldahl (2006).

commonly used measures of competition.

Our results suggest that lessen regulation increasing domestic product-market competition is positively associated with R&D intensity and patenting. Besides, we find that increasing foreign competition leads to higher patenting, but have mixed effects on R&D intensity in our baseline specification. Finally, using the sub-indicators of domestic and foreign competition regulation, the effects can be partially explained by market competition policies that reduce barriers to new entrants and bureaucracy costs, while tariff and non-tariff barriers had opposite effects according to our innovation measures.

The main challenge to our identification strategy is the possible reverse causality between innovation and competition reforms as well as the existence of omitted variables. We address these issues in several ways. First, to address endogeneity issues we use aggregate measures of competition regulation in European and non-European countries as an instrument for regulation in a particular country. Our conclusions are robust to the instrumental variable (IV) specification with larger point estimates than OLS estimates. Second, the estimates are stable to the inclusion of lagged competition regulation indicators that reduce potential reserve causality between competition and innovation intensity. Finally, our results are robust to alternative specifications, controlling for confounding factors such as import intensities and foreign R&D.

Domestic and foreign competition might have a different magnitude in enhancing innovation. Related literature does not compare the effect of the source of competition reforms. In addition to challenging the ambiguous empirical findings on the relationship between innovation and regulation, this chapter goes even further in empirical identification. Instead of findings based only on regression identification and reduced-form[4], we use causal structure methodology that allows discovering endogenously causal relations and ordering determinants of innovation. Differentiating between domestic and foreign competition regulations (i.e., to the extent which regulation directly causes innovation) might reconcile conflicting findings and the importance of underlying mechanisms. We explore causal relations and identify which source of competition regulations are direct causes of innovation intensity. Specifically, we rely on a Directed Acyclic Graph (DAG) strategy that is based on search algorithm (Pearl, 1995). The DAG suggests that domestic regulation enhancing product-market competition is the only direct cause of innovation intensity, while foreign regulation indirectly impacts R&D intensity and

[4]See for example Nickell (1996), Blundell et al. (1999), Nicoletti and Scarpetta (2003), Aghion et al. (2005), Griffith et al. (2010), and Bloom et al. (2016).

patenting at the country-level. Also, the magnitude of the causal effect of product market regulation is highly similar to the point estimate through IV specification. These results point out mechanisms in the innovation-competition relationship, leading important policy implications.

The remainder of the chapter is organized as follows. Section 2 presents the related literature and states empirical hypotheses. Section 3 presents the main variables, data sample and discusses our identification strategy. Section 4 discusses our results and robustness tests. Section 5 concludes and discusses the policy implications of our results.

2 Related Literature and Hypotheses

2.1 *Domestic Competition and Regulation*

Regulation of competition in the product market is to facilitate the entry of new firms or to protect existing monopoly positions. Efficient regulation on product market (PMR hereafter) can encourage firms to invest in technological innovation, R&D activities at each step of innovation process (Bourlès et al., 2013; Ciriaci et al., 2016). Lessening excessive barriers in PMR might facilitate competition dynamics among competitors through higher firm entry rates and stimulate the creation of new knowledge (Andrews and Criscuolo, 2013). Finally, less stringent regulation can improve the firms' dynamic and turnover, and the growth of efficient firms.

Empirical literature into a suitable degree of competition on the PMR appears very voluminous. This strand of the literature tends to support the idea that less burden regulation could increase competitive pressure. Two important contributions derived from Blind (2012) and Westmore (2013) have provided evidence on the impact of legal regulation of competition based on cross-country panels. On the one hand, Westmore (2013) adopts the PMR indicator[5] to evaluate the effect of anti-competitive regulation on R&D expenditures and patenting intensity. Westmore (2013) reports a significant and negative correlation, suggesting that pro-competition reforms to product market regulation are associated with an increase in innovation. In addition, he supports that reducing excessive PMR favors knowledge spillovers on domestic patenting, suggesting that pro-competitive reforms might spur firms to accumulate a stock of knowledge from

[5] Product Market Regulation: This indicator updated by Wölfl et al. (2009) enables the analysis of changes in individual regulatory policies in OECD countries and covers general regulatory issues concerning public control and prices control, legal and administrative barriers to entry, and barriers to trade and investment.

foreign countries. On the other hand, from survey data, Blind (2012) does not support the positive argument that pro-competition reforms drive innovation. In contrast, the author concludes that a long-term reduction of pressure is a positive influencing factor for innovation, in line with Schumpeter's argument.

Further evidence has also been provided at the industry level. Nicoletti and Scarpetta (2003) among others investigate on 18 OECD countries, 23 two-digit manufacturing and service sector over 1984-1998 the impact of competition thought policy regulations that directly affect market competitiveness. They find a positive influence of less stringent barriers to entry and lower level of state control on productivity growth and move forward the technological frontier, in particular in laggard countries. Their findings suggest that reforms that enhance competition on product-market improve adoption of new technologies and innovation. Using OECD-derived regulation indicators with a DID specification, Bourlès et al. (2013) provide evidence of a negative impact of upstream regulation on the productivity growth measured through multifactor productivity, thus showing the increase in interconnections between services and the manufacturing sector.

Aligned with these findings, several studies confirm at the firm level that competitive market have a positive effect on innovation intensity (e.g., Blundell et al. 1993, Nickell 1996, and Goldschlag and Tabarrok 2018). More recently, empirical findings support that reducing regulatory and administrative barriers (i.e. procedures for starting a business, cost of closing) improve business dynamic and affect positively productivity (Andrews and Cingano, 2014; Canton et al., 2014).
However, Aghion et al. (2005) empirically demonstrate the existence of an inverted U-shaped relation between competition and the number of US patents granted. This result implies that at low levels of competition, an *"escape competition"* effect dominates, while the *"schumpeterian"* effect is dominant when the initial levels are already high. Extensive subsequent findings supported the inverted U-shaped relationship (Negassi et al., 2019; Tingvall and Poldahl, 2006). But these findings rely on the competition measure, differences among countries and industries as well as the estimated time period.

Consistent with the discussion above, we expect a positive impact of competition-increasing product market regulation on R&D and patenting intensities at the country level.

Hypothesis 1: Lessen domestic market regulation promotes competitive pressure and increase innovation intensity at the country level.

2.2 Foreign Competition and Regulation

The effect of trade liberalization has a wide range of impacts on innovation such as improve the firm's exposure to the foreign stock of knowledge, facilitating the diffusion of ideas as well as technology transfers and upgrading quality (Coe and Helpman, 1995; Bloom et al., 2016). In addition, trade liberalization induces higher foreign competition pressure Melitz (2003). However, nascent empirical literature does not seem to converge on a common conclusion on the effect of competition via imports (Autor et al., 2016; Bloom et al., 2016; Akcigit and Kerr, 2018).

A first strand of the literature proposed a theoretical framework of monopolistic competition with heterogeneous firms characteristics (Melitz and Ottaviano, 2005) investigates the effect of trade liberalization and the *demand-side* effect (i.e., market size). Melitz and Ottaviano (2005) suggest a short-term negative impact on mark-ups, but a positive impact on aggregate productivity. In the same line, several recent papers confirm the potential benefit to trade liberalization, enhancing incentive firms to innovate at long-term (Perla et al., 2015; Impullitti and Licandro, 2018).
The second strand of the literature combines theoretical foundations of heterogeneous firms and monopolistic competition with step-by-step innovation (Aghion and Howitt, 1998). Looking into the effect of import competition, these papers provide evidence of positive and negative impacts according to the distance from the technological frontier. On the one hand, a negative effect of competition on firms behind the technology frontier while, on the other hand, the most productive firms tend to respond positively to an import shock (Aghion et al., 2017; Akcigit and Kerr, 2018).
Finally, recent contributions examine the effect of import competition resulting from China shock on US and European firms. These two works come to conflicting conclusions. On the one hand, Bloom et al. (2016) demonstrate that lower import tariff rates with low technology countries as China increase strategic investments in R&D by reducing the opportunity cost. On the other hand, Autor et al. (2016) find at the firm level several negative impacts. First, following an increase in imports of products from China, they report a negative impact on innovation input and output, but also on firms' dynamics with a decrease in employment and sales.
However, these findings rely on the theoretical framework or are limited by unilateral trade liberalization shock (Coelli et al., 2016). Griffith et al. (2010) investigate the impact of entry into the Single Market Program in Europe, suggesting that the adoption of this single program increase competition between countries and an increase in innovation and productivity. Similarly, Coelli et al. (2016) find that multilateral change in trade policy (i.e., 60 countries) is associated with an increase in firm patenting.

Based on the discussion above, we state the following hypothesis:

Hypothesis 2: Lessen foreign market regulation promotes competitive pressure and increase innovation intensity at the country level.

3 Data and Empirical Strategy

3.1 *Measuring Innovation*

For our main sample, we combine data from several sources into a balanced panel dataset, which covers 25 OECD countries for the period 1995-2015[6].

To measure innovation intensity, we collect country-year observations from the latest version (i.e., edition 2017) of the OECD Science and Technology Indicators Database (MSTI) and the OECD Triadic Patent Families Database. Additional information on innovation outcomes are provided in Appendix 1.A. These two databases provide detailed information on Research and Development (R&D) expenditures for the manufacturing sector and the number of patents registered with the three major patent offices: EPO, JPO, and USPTO. In line with the empirical literature, our primary measure of innovation is R&D intensity, defined as nominal business R&D expenditures over nominal GDP. The second measure is the count of granted triadic patent per capita, transformed in logarithm where Patent denotes the count of patents owned by the resident of each country measuring in millions of inhabitants[7]. Using triadic patents has the advantage that not be biased according to regional legislation and that if a firm has protected its invention in the three main offices, it is possible to assume that the invention is of major importance (Aghion et al., 2017). However, measuring innovation raises some issues, in particular at the country level. Several issues are regularly discussed in the literature but have long been used as an indicator for innovative activities (Griliches, 1990; Hall et al., 2010). Following the OECD's Frascati Manual (2015) and the Oslo Manual (2005), R&D expenditures are an input in the innovation process and the count of patents is a proxy for intermediate innovation output (Mairesse and Mohnen, 2010). Consequently, these measures provide an imperfect indicator of innovation and are not useful outside

[6]The sample includes: Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Mexico, Netherlands, Norway, Poland, Portugal, Slovak Republic, Spain, Sweden, Switzerland, Turkey, United Kingdom, and the United States

[7]Given the existence of zero and low count of patents for some countries and years (e.g. Turkey), our second measure of innovation intensity takes the following form Patent=log(1 + Patent). This approach has been used in the literature (e.g., Bloom et al. 2016 and Aghion et al. 2005).

of the manufacturing sector. Not all firms invest in fundamental and applied R&D activities or filed a patent for their inventions. On the one hand, firms can conduct other activities, such as get intangible assets. On the other hand, patents measure successful inventions but they can be protected by informal means, such as secrecy or lead-time over competitors[8]. However, R&D expenditures and the count of patents have been regularly collected in a large sample of countries, usually on an annual basis, and they are readily available. Furthermore, to our knowledge, it is the only international data source which provides comparable estimates of business R&D expenditures and technological progress.

3.2 *Measuring Market Regulation*

Following Griffith et al. (2004) and Aghion et al. (2009), we focus on legal rules that capture market regulations. Therefore, we focus on framework conditions that transcribe both domestic's market and foreign competition. Additional information on variables used in the main specification are provided in Appendix 1.B. These indicators are provided by the Fraser Institute's Economic Freedom of the World Database. There provide indicators of economic freedom in Business regulations and Barriers to trade on a scale of 0 to 10. To interpret these indicators economically, low value (i.e., near to 0) indicates stringent regulation, while higher value (i.e., near to 10) refers to lessen regulation.

The Business Regulations indicator measures the extent to which market regulation restricted domestic competition. It is based on a subset of indicators: the ease of starting a business and the cost associated with time spent on bureaucracy procedures. The rationale for using these indicators is that more stringent market regulation might be associated with a lower innovation intensity. The starting a business indicator measures the extent to which firm entry is restricted through the perception of decision-makers, which we use to access the effects of new entrants competition on innovation intensity. Bureaucracy costs represent the time spent with administrative procedures that might lengthen the process of starting a business or slow down the growth of incumbent firms. Finally, we include an index of Trade Regulations composed of a subset of indicators: average import tariff and non-tariff trade barriers that can hinder exchange of good, technology transfers and competition from foreign competitors.

Previous literature estimating the effects of competition on innovation and produc-

[8] A large literature based on surveys highlights that patent protection is not the optimal method to protect and capture returns to innovation, except in high-technology sectors, such as pharmaceuticals, biotechnology or chemicals (Mansfield, 1986; Moser, 2005; Hall and Harhoff, 2012)

tivity outcomes has used several measures including mark-ups (Griffith et al., 2004), market concentration, through Herfindahl or Lerner index (Aghion et al., 2017), or product market regulation (PMR) indicators provided by the OECD. However, they may be concerned about endogeneity issues. For example, increasing competitive pressure on the domestic market probably leads to reduce market concentration. In addition, by a reallocation effect from less efficient to most efficient firms, profits and mark-ups are impacted differently depending on the firm structure. The rationale to consider these economic regulations as exogenous is not straightforward (Cette et al., 2017). The measures used in this chapter, based on surveys of the assessment of the business environment have at least two advantages relative to previous empirical evidence. First, our indicators minimize the endogeneity concern because they are based on opinions and some potential underlying policies that affect competition, instead of directly measuring market competition (Bourlès et al., 2013). The second advantage is to be available at an annual frequency and at five-year intervals before 2000[9]. In contrast to previous literature, the choice of these explanatory variables is motivated by the fact that are available on long time horizon, in contrast to OECD's indicators, which develops similar indicators (PMR) available from 1998 to five-year intervals and end in 2013 (Égert, 2016).

In order to control for factors influencing competitive pressure and for time-varying determinants of innovation, several control variables are included in our main specification (Teece, 1996). First, the relationship between innovation and competition might be overestimated if they are both related to the business cycle, leading to a pro-cyclical relationship. To control for this issue, we include the GDP Growth that corresponds to the annual percentage growth rate of the country's GDP based on constant price U.S. dollars PPP (2010). Second, innovation might be driven by the country's comparative advantage in an industrial sector, confounding our main estimates. Following Acharya et al. (2013), we control for comparative advantages using the ratio of value-added (VA) in the manufacturing sector relative to the total country's VA. These control variables are from the World Bank WDI Database. Finally, another concern is that market regulations in a given country may be correlated with additional regulations (Acharya et al., 2013; Buccirossi et al., 2013). Therefore, we control for the legal system's quality, which aggregates information on rule of law, protection of intellectual property, and the efficiency of the juridical system. This variable is drawn from the Fraser Institute Database and is defined on a scale of 0 to 10, with higher values indicating better institutional quality.

[9] To address this concern, we implement a linear interpolation for each indicator between 1996 and 1999. On our estimation period, few changes appear over time describing characteristics variables with low within variance.

3.3 *Cross-country Characteristics*

Table 1.1 – Summary Statistics.

Variable	Description	Source	Min	Mean	Max	Std.
Innovation Variables						
R&D Intensity	R&D expenditures over GDP	OECD STI	0.037	0.986	3.148	0.712
Patent	Triadic ln(1+ Patents) registered in patent offices per capita	OECD Patent	0.031	2.782	4.993	1.427
Product-Market Regulation						
Business Reg.	Regulatory constraints on product markets, average of 6 sub-components (0=least free; 10=free)	Fraser Institute	3.906	7.005	8.853	0.997
Bureaucracy Cost	Cost of bureaucratic procedures (0=least free; 10=free)	Fraser Institute	1.923	6.715	10.000	1.820
Starting Business	Stringency to start a Business index (0=least free; 10=free)	Fraser Institute	3.433	8.714	9.948	1.363
Trade Reg.	Regulatory constraints on international trade (0=least free; 10=free)	Fraser Institute	3.683	7.842	9.759	0.854
Tariff Barriers	Import tariff barriers (0=least free; 10=free)	Fraser Institute	5.604	8.141	9.917	0.897
Non Tariff Barriers	Average tariff rate to import (0=least free; 10=free)	Fraser Institute	3.683	7.015	9.685	1.171
Control Variables						
ΔGDP	Aggregate annual GDP growth rate at market prices based on constant 2010 US	World Bank WDI	-9.132	2.445	25.557	3.042
V.A	Manufacturing value added over GDP	World Bank WDI	7.370	18.144	36.961	5.121
Legal Integrity	Measurement of the efficiency of legal system (0=least free; 10=free)	Fraser Institute	4.222	7.376	9.278	1.242

Note: This table presents the summary statistics for our analysis sample, a balanced panel of 525 observations in 25 OECD countries spanning 1995-2015.

Table 1.1 reports descriptions, data sources, and summary statistics of the main variables used in this analysis[10]. First, there is substantial variation in innovation measures across OECD countries during our sample period, with R&D intensities that range from 0.6 percent of GDP (Mexico) to 3.35 percent (Japan) and the count of granted triadic patent per capita that ranges from 0.031 (Turkey) to 4.993 (Japan). Second, we highlight preliminary relationships between market competition regulation and innovation intensity. In Figure 1.1, we show the scatter plot of all country-year data points of the R&D intensity and the count of patent per capita distribution. The left-hand sub-figures refer to business regulations as a measure of domestic competition, where the vertical axes refer to innovation measures and the horizontal axes to the business regulations. The right-hand sub-figures refer to trade regulations as a measure of foreign competition, where the vertical axes refer to innovation measures and the horizontal axes to the trade regulations. Overall, the linear prediction from the regression of innovation intensity on the market regulation indicators is consistent with the positive relationship between innovation intensity and competition-enhancing regulations. Furthermore, these patterns are consistent with the coefficients correlation report in Table 1.2.

Table 1.2 – Correlation Matrix.

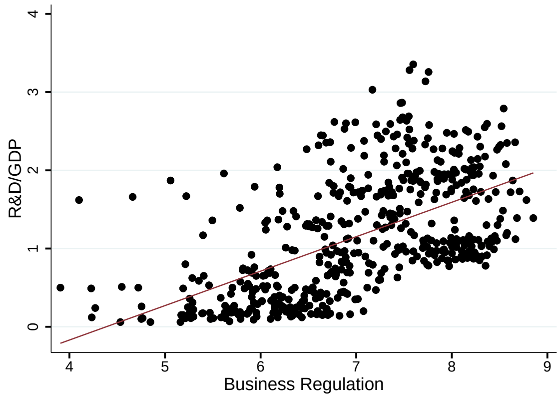
	R&D Intensity	Patent	ΔGDP	V.A	Legal Integrity	Business Reg.	Trade Reg.
R&D Intensity	1						
Patent	0.781	1					
ΔGDP	-0.115	-0.171	1				
V.A	0.188	0.122	0.091	1			
Legal Integrity	0.582	0.698	-0.033	0.279	1		
Business Reg.	0.573	0.602	0.017	0.196	0.710	1	
Trade Reg.	0.256	0.451	0.042	-0.007	0.548	0.538	1

Note: This table presents the correlation matrix between our outcomes and variables of interests, which we use in our main identification strategy.

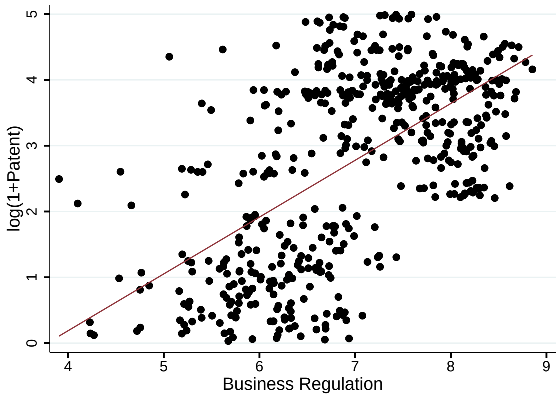
3.4 *Empirical Strategy*

In this chapter, we focus on the impacts of market regulation on innovation intensity at the country level. First, we estimate separately panel fixed-effects specifications with innovation measures as dependent variables and our measures of domestic and foreign market regulations as independent variables. Our market regulation variables are included step-by-step in order to not overburden the econometric estimation. Then, our specification is augmented with each sub-indicator in order to capture various channel through which innovation activity is impacted. The baseline specification is as follows:

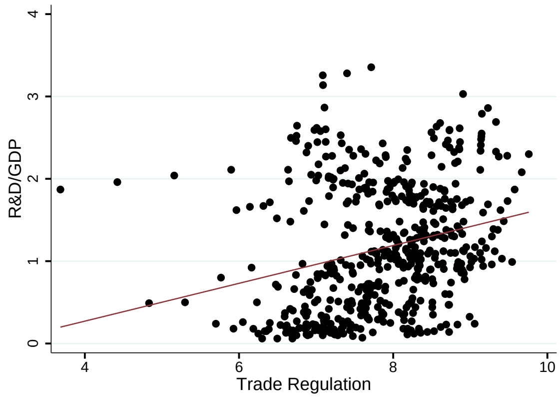
[10]For readability, further details on innovation and regulation (business and trade regulation indicators) trends are provided in the Appendix.



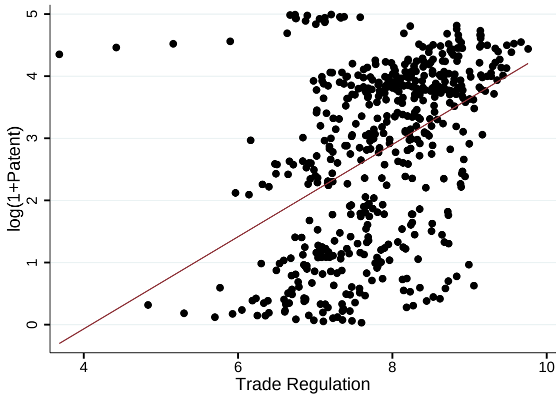
(a)



(b)



(c)



(d)

Figure 1.1 – Scatter plot of Innovation Intensity on Domestic and Foreign Competition Regulation.

Notes: This figure shows the relationship between the business, trade competition regulation, and country innovation. Panels A and B show the relation between the business regulation indicator with R&D and patent intensities, while Panels C and D show the relation with trade regulation indicator. The circles indicate all 525 country-year data points between 1995 to 2015 in our analysis sample of 25 OECD countries.

$$y_{ct} = \alpha + \beta_1 Reg_{ct} + \beta_2 X_{ct} + u_c + u_t + \varepsilon_{ct} \tag{1.1}$$

where y_{ct} denotes our main dependent variables that measure innovation intensity from country c in year t, including *R&D intensity*, and *Patent*. Reg_{ct} is the market regulation indicators for country c, measuring the stringency of domestic and foreign competition regulation. The main coefficient of interest is β_1 that denotes the effect of market regulation on the dependent variable of interest. X_{ct} is a set of control variables, u_c and u_t are country and time fixed effects. Different OECD countries have experienced different level of innovation intensity over the years that are not directly correlated with market regulations and competition, but might be correlated with institutional environment (Aghion et al., 2005). Adding country and time fixed effects allows us to control for time-invariant unobserved factors at the country level. Robust (Huber-White) standard errors are used.

Using fixed-effects transformation (i.e., within transformation) has the advantage to provide unbiased estimates if omitted variables are correlated with explanatory variables. However, fixed-effects transformation is less efficient for the estimation of rarely changing variables, resulting in biased point estimates (Wooldridge, 2010; Hsiao, 2003). This is particularly relevant for variables that described the political and legal environment. Thus, an identification strategy by using fixed-effects transformation could lead to biased or underestimated coefficient of interest.

Following Plümper and Troeger (2007), we implement a three-stage estimator with vector decomposition in the third stage. This estimator provides an efficient estimate of time-varying variables in addition to an unbiased estimate of rarely changing variables through pooled least square[11]. In our main specification, the rarely changing variables are Business Regulation and Trade Regulation as well as sub-indicators, which exhibit larger "between" than "within" variance, providing justification for using FEVD estimator.

Thus, we estimate the following three stages specification:

First Stage:

$$y_{ct} = \alpha + \sum_{m=1}^{M} \beta_m Reg_{cm} + \sum_{k=1}^{K} \beta_k X_{ct} + u_c + u_t + \varepsilon_{ct} \tag{1.2}$$

where the Reg_m are the rarely changing variables and X_{ct} are the time-varying variables. In the first stage, the FEVD estimator estimates a fixed-effects model to produce unit fixed effects $\hat{u_c}$.

Stage Two: In the stage two, the estimated unit effects from stage one are regress on rarely changing variable, in order to decompose the unit effects in two parts, an explained and unexplained h_c.

$$\hat{u_c} = \sum_{m=1}^{M} \beta_m Reg_{cm} + h_c \tag{1.3}$$

[11] Plümper and Troeger (2007) provides two conditions for efficient point estimates with precisely estimated standard errors. First, FE and FEVD estimator are preferable to the random effects estimator (GLS) for which individual effects are assumed to be uncorrelated with the independent variables. Second, FEVD becomes more efficient when the within variance close to zero and the ratio of the between-to-within variance that exceeds 2.8 for at least one of our independent variable.

where h_c=$\hat{u}_c$ - $\sum_{m=1}^{M} \beta_m Reg_{cm}$.

Stage Three: Finally, in the third stage, specification of the first stage is re-estimated through pooled OLS without unit fixed effects (i.e., country fixed effects) but augmented with the unexplained part h_c obtained in the second stage as follows:

$$y_{ct} = \alpha + \sum_{m=1}^{M} \beta_m Reg_{cm} + \sum_{k=1}^{K} \beta_k X_{ct} + \delta h_c + u_t + \varepsilon_{ct} \tag{1.4}$$

Nevertheless, FEVD estimator is subjected to controversial on inferences for estimated coefficients[12]. Therefore, we use FEVD estimator for comparison to OLS.

4 Results

4.1 *Main Results*

In Table 1.3 we report the average effect of competition-enhancing product market regulation on R&D intensity (Panel A) and the natural logarithm of patents corrected to country size (Panel B). We report point estimates through OLS and FEVD for a balanced sample of 525 country-year observations in 25 OECD countries for the period 1995-2015.

Our main finding is that the point estimate for the business regulation indicator is positive[13] and statistically significant at conventional level. The point estimate in column (1) of Panel A suggests that increasing product market competition by one standard deviation (0.997) increases R&D intensity by 0.062 (0.062×0.997). The average R&D intensity in the sample estimation is 0.986. Thus, the R&D intensity increases by 6.3 percent. Our main finding remains if we estimate the effect of the competition-increasing product market regulation through FEVD estimator (columns 4 and 6) which produces an efficient estimate of rarely changing variables. Note that the point estimate increase in magnitude relative to OLS estimation. We now turn to the relationship between business regulation and patenting activities in Panel B of Table 1.3. Both in OLS and FEVD specifications, we find a positive and significant effect of market competition on the number of patents granted. Our results support Hypothesis 1 states in Section 2. Our findings are consistent with an escape-competition effect and innovation levels increased when competition-enhancing product market regulation increased (Aghion et al., 2005;

[12]For example, see Greene (2011) and Breusch et al. (2011).

[13]The indicators take a value that ranges on a scale of 0 to 10, with higher values indicating lessen regulation increasing domestic and foreign competition.

Table 1.3 – Baseline Results.

	OLS			FEVD		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A. R&D Intensity						
Business Reg.	0.063**		0.053*	0.348***		0.363***
	(0.029)		(0.028)	(0.011)		(0.010)
Trade Reg.		0.040*	0.018		0.184***	-0.036***
		(0.024)	(0.022)		(0.011)	(0.009)
ΔGDP	-0.005	-0.006	-0.006	-0.005	-0.006	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
V.A	0.017***	0.019***	0.018***	0.017***	0.019***	0.018***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Legal System	-0.0006	0.012	-0.0008	-0.0006	0.012	-0.0008
	(0.022)	(0.020)	(0.022)	(0.032)	(0.032)	(0.032)
FEVD error term	–	–	–	1	1	1
Panel B. Patent						
Business Reg.	0.174***		0.111***	0.782***		0.649***
	(0.029)		(0.030)	(0.022)		(0.016)
Trade Reg.		0.161***	0.113***		0.656***	0.263***
		(0.025)	(0.024)		(0.023)	(0.017)
ΔGDP	-0.006	-0.008	-0.008	-0.006	-0.008	-0.008
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
V.A	-0.002	0.001	0.00009	-0.002	0.001	0.00009
	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Legal System	0.107***	0.134***	0.105***	0.107***	0.134***	0.105***
	(0.035)	(0.038)	(0.033)	(0.029)	(0.030)	(0.029)
FEVD error term	–	–	–	1	1	1
Country effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	525	525	525	525	525	525

Notes: This table presents OLS and FEVD estimates of the impact of competition regulation on innovation intensity. Columns (1-3) show the estimated impact through OLS of competition regulation on R&D intensity (Panel A) and columns (4-6) show the estimated through FEVD of competition regulation on patent intensity (Panel B). Robust standard errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01.

Griffith et al., 2010)[14].

Our second finding is a mixed effect of trade regulation on innovation intensity. In columns 2 and 4 of Panel A, estimated coefficients are positive and statistically significant but turn out not different from zero (column 3) or negatively correlated (column 6) with R&D intensity in specifications that include both business and trade regulation indicators. In contrast, we find a positive effect of the trade competition on patenting

[14] As mentioned in the introduction, the chapter assumes and estimates a linear relationship between innovation intensity and competition regulation, although we do not examine an inverted-U relationship. As supported by Aghion and Howitt (1998) and Aghion et al. (2005), both escape-competition and Schumpeterian effects might coexist. However, consistent with previous findings, the escape-competition effect dominates in the linear relationship (Griffith et al., 2010; Aghion et al., 2005).

intensity in Panel B of Table 1.3. This is consistent with previous empirical evidence, in particular, for European countries exposed to import competition from China (Bloom et al., 2016). Our results partially confirm Hypothesis 2. Point estimates for control variables have the expected sign and conform to previous evidence. In particular, we find that the GDP growth is negatively associated with innovation intensity although insignificant, while we find that manufacturing value-added has a positive and significant association with R&D intensity. The positive correlation between innovation intensity and manufacturing value-added reflects variation in the propensity to innovate and technological opportunities that differ across industries. Finally, the quality of institutions measured through legal system indicator in order to account for the effectiveness of competition regulation has opposite sign according to our measure of innovation intensity. We show the point estimate on the legal system is positively associated with increased in patenting intensity, while is not statistically different from zero for R&D intensity.

We then examine the effect of the sub-indicators of domestic and foreign competition. We use the ease of starting business and bureaucracy cost as our main measure of domestic market regulations. In addition, we also investigate average tariff and non-tariff barriers to competition from foreign competitors. We estimate specification (1) and report the results in Table 1.4. In column (1) of Panel A, the point estimate suggests that lessen barriers to new entrants by one standard deviation is associated with a 0.054 increases in R&D intensity. In column (2), the point estimate on bureaucracy cost is positively associated with R&D intensity, suggesting that reducing the administrative burden by one standard deviation increases R&D intensity by 0.025. In column (3), we examine the effect of the average tariff barriers and find a negative and statistically significant coefficient at the 1 percent level on R&D intensity, while the point estimate on non-tariff trade barriers is not statistically different from zero (column 4). A possible explanation for this negative effect of reducing tariff barriers is the direct positive effect with imported products, increasing knowledge spillovers, thereby reducing incentives to innovate. In summary, the results in Panel A of Table 1.4 confirm our baseline results and show that enhancing the reforms to promote market competition leads to an increase in R&D intensity while lowering tariff barriers deters domestic R&D intensity.

In Panel B of Table 1.4, we replace the dependent variable with the natural logarithm of patents corrected to country size. Our results help to check whether product market sub-indicators impact otherwise the innovation output. We show similar results to those obtained using R&D intensity as dependent variable with the exception of sub-indicators of trade regulation. The point estimate in column (3) of Panel B is insignificant, indicating

Table 1.4 – Sub-Indicators.

	OLS			
	(1)	**(2)**	**(3)**	**(4)**
Panel A. R&D Intensity				
ΔGDP	-0.003	-0.004	-0.004	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)
V.A	0.022***	0.024***	0.022***	0.024***
	(0.005)	(0.005)	(0.005)	(0.005)
Legal System	0.030	0.041*	0.013	0.039*
	(0.021)	(0.021)	(0.021)	(0.021)
Starting Business	0.040**			
	(0.020)			
Bureaucracy Cost		0.019**		
		(0.009)		
Tariff Barriers			-0.070***	
			(0.020)	
Non-tariff Barriers				0.005
				(0.017)
Panel B. Patent				
ΔGDP	-0.003	-0.007	-0.005	-0.007
	(0.006)	(0.006)	(0.006)	(0.006)
V.A	-0.004	0.0007	-0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.005)
Legal System	0.137***	0.168***	0.163***	0.131***
	(0.040)	(0.044)	(0.045)	(0.043)
Starting Business	0.111***			
	(0.020)			
Bureaucracy Cost		0.038***		
		(0.009)		
Tariff Barriers			-0.009	
			(0.021)	
Non-tariff Barriers				0.094***
				(0.016)
Country effects	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes
Obs.	525	525	525	525

Notes: This table presents OLS estimates of the impact of sub-indicators of competition regulation on innovation intensity. Panel A shows the estimated impact through OLS of sub-indicators of competition regulation on R&D intensity and Panel B on patent intensity. Robust standard errors in parentheses.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

no effect of tariff barriers on patenting activities. In contrast, the estimated coefficient in column (4) is positive and statistically significant, suggesting that reducing non-tariff trade barriers by one standard deviation is associated with a 0.109 increase in patenting. Thus, this represents 3.9 percent at the mean value of patents.

Overall, enhancing regulation that increases domestic competition is associated with an increase in innovation intensity at the country level. In contrast, our results imply a negative association between foreign competition and R&D intensity, but reforms that reduce non-tariff barriers on patenting and confirm our baseline results in Panel B of Table 1.3.

4.2 *Robustness Tests*

To test the reliability of the baseline results in Table 1.3, we conduct several robustness tests. First, an important issue with our main specification is the potential endogeneity problem of market regulation due to reverse causality bias as well as omitted variables (Aghion et al., 2005). For example, R&D expenditures and successful innovations might increase economic rents and market concentration, reducing competition among firms. This is more likely to downward biased OLS estimates as incumbent firms and successful innovations increase. Moreover, variation in trade regulation may reflect governments' perception of domestic competition and technology frontier to support foreign competition, biasing OLS estimates. To address the endogeneity issues, we propose an alternative identification strategy using an instrumental variable (IV) approach. Specifically, we use a two-stage least squares (2SLS) strategy. Following Buccirossi et al. (2013), Ayyagari et al. (2008), we instrumented competition-increasing product market regulation with the average value of these regulations in other countries[15]. In particular, we use the average value based on country-group (i.e., European and non-European). The exclusion restriction is that competition regulation in a country is more likely to be correlated with trends in competition regulations in the same geographical or jurisdiction region[16], but are uncorrelated with innovation intensity in the country. The results of these IV estimations are reported in Panel A of Table 1.5. The estimated coefficients on the IV are positive and statistically significant at the 1 percent level with larger point estimates than OLS in Table 1.3. This OLS bias is consistent with the idea that positive product market regulation in the same geographical or jurisdiction region increases the probability of increasing competition for a given country. Thus OLS underestimates the innovation intensity response to competition-increasing product market regulation. In addition, instruments are highly significant with a reported F-statistic that exceeds 10[17].

[15] Instrumental variable identification based on group averages is described in Angrist and Krueger (2001) and Hausman (1997).

[16] For example, in 1992 the European Union has implemented a large-scale internal reform: the Single Market Program (SMP). The SMP aimed at reducing internal barriers within the EU with the objective to increase the movement of products and production factors, fostering competition, innovation, and productivity growth.

[17] The joint significance of excluded and included instruments in the first stage exceeds the critical value of weak instruments proposed by Stock and Yogo (2005).

Table 1.5 – Robustness Tests.

	R&D intensity		Patent	
	(1)	(2)	(3)	(4)
Panel A. IV.				
Business Reg.	0.408***		0.304***	
	(0.082)		(0.084)	
Trade Reg.		0.278***		0.215***
		(0.060)		(0.067)
ΔGDP	-0.009**	-0.011**	-0.008	-0.010
	(0.004)	(0.004)	(0.005)	(0.006)
V.A	0.015***	0.023***	-0.003	0.002
	(0.005)	(0.005)	(0.004)	(0.005)
Legal System	-0.119***	-0.035	0.062*	0.123***
	(0.042)	(0.026)	(0.036)	(0.032)
First Stage F-statistic	35.4	36.1	35.4	36.1
Panel B. Including Lagged Regulation Indicators				
Business Reg.$_{t-1}$	0.086***		0.179***	
	(0.029)		(0.032)	
Trade Reg.$_{t-1}$		0.045*		0.158***
		(0.024)		(0.025)
ΔGDP	-0.005	-0.005	-0.005	-0.006
	(0.004)	(0.004)	(0.005)	(0.006)
V.A	0.016***	0.017***	-0.002	0.0006
	(0.005)	(0.005)	(0.004)	(0.005)
Legal System	-0.012	0.006	0.124***	0.158***
	(0.022)	(0.023)	(0.035)	(0.040)
Panel C. Including Additional Control Variables				
Business Reg.	0.064**		0.163***	
	(0.027)		(0.031)	
Trade Reg.		0.058***		0.146***
		(0.020)		(0.025)
ΔGDP	-0.003	-0.004	-0.010*	-0.012*
	(0.005)	(0.004)	(0.006)	(0.006)
V.A	0.018***	0.019***	-0.003	0.0008
	(0.005)	(0.005)	(0.004)	(0.005)
Legal System	0.012	0.023	0.110***	0.139***
	(0.022)	(0.020)	(0.036)	(0.040)
Import Penetration	2.065***	2.242***	0.025	0.472
	(0.496)	(0.512)	(0.539)	(0.563)
Foreign R&D	-0.504***	-0.557***	0.476***	0.346**
	(0.095)	(0.096)	(0.149)	(0.151)
Country effects	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes
Obs.	525	525	525	525

Notes: This table presents robustness tests of our main results. Panel A estimates the competition regulation impact on innovation intensity by 2SLS. This specification instrument for competition regulation using the average value of the regulation indicators in group-member (i.e., European vs Non-European Countries). Panel B shows the results using the lagged indicator for business and trade regulation to mitigate reverse causality. Panel C includes an additional set of control variables: import penetration ratio and the foreign stock of R&D. Robust standard errors in parentheses.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

To control for reverse causality between competition policy and innovation intensity, we include the lagged value of regulation indicators in Panel B of Table 1.5. This approach relies on the assumption that the lagged indicators are unrelated to the error terms in specification (1) (Griffith et al., 2004). Estimated coefficients are relatively similar and very close in magnitude to OLS estimates in Table 1.3.

Finally, competition-increasing product market regulation might be driven by omitted variables that are correlated to other competition-enhancing policies that could affect innovation intensity. In Panel C, we include control variables that may be correlated to market regulation: import penetration ratio and foreign stock of R&D[18]. Our results remain robust across all specifications. Note that import penetration is positively associated with R&D intensity[19], but insignificant in specification with the natural logarithm of patent corrected to country size. In contrast, the estimated coefficient on the foreign stock of R&D is always negatively associated with R&D intensity while increasing the foreign stock of R&D is associated with an increase in patenting[20]. This tends to support our baseline results and our confidence in the mitigation of endogeneity issues.

4.3 *Direct and Indirect Causal Effect of Competition*

Our main focus in this chapter is to identify the causal determinants of innovation intensity and compare the results from previous estimates. The relationship between competition and innovation has grown in importance on the endogenous growth literature, but also for policymakers. However, this issue has led to contrasting theoretical arguments and empirical evidence. Following Ayyagari et al. (2013) and Ayyagari et al. (2008), we use Directed Acyclic Graph (DAG) that allows us to explore the potential direct mechanism between competition-increasing product market regulation and innovation as well as causal relations among market regulation measures[21]. Unlike from different studies that investigate the impact of competition on innovation, using DAG methodology has several advantages over classical econometric specifications. DAG

[18]In these specifications, we control for the domestic demand of goods and services and R&D is satisfied by foreign producers. The import penetration ratios are defined as the ratio between the value of imports as a percentage of total domestic demand and are drawn from the OECD Trade Indicators Database. The R&D foreign stock measure we use information on trade-weighted of all other partner's countries, where weights are drawn from the IMF Trade of Statistics database (Westmore, 2013).

[19]For example, one standard deviation in import penetration increases R&D intensity by 0.184 (2.144×0.086), column (3) Panel B.

[20] For example, a one standard deviation increase in the foreign stock of R&D increases patenting by 0.149, column (6) Panel B.

[21] Several studies use Extreme Bound Analysis (EBA) to test the main determinants of theoretical frameworks as well as the robustness of econometric specifications. For example, Barro (1991), Levine and Renelt (1992), Xavier et al. (1997) use EBA to test main determinants of economic growth, and Ayyagari et al. (2013) to compare DAG's results from EBA methodology.

can endogenously and non-parametrically specify the causal ordering of the entire set of variables by producing a graph of robust causal relations. (Ayyagari et al., 2013; Spirtes et al., 2000). Specifically, DAG allows us to examine determinants of innovation that have *(i)* direct effects, variables that have *(ii)* indirect effects for another variable and those that do not have *(iii)* causal effect. Additionally to regression estimates, using DAG allows validating empirical findings.

The causal model corresponds to a set of random observed and unobserved variables X={X_1 ; $\cdots$; X_n} associated with independent error terms ε={ε_1 ; $\cdots$; ε_n}. The causal relationships between the variables X are represented by a graph G in which nodes are connected by directed edges E according to the joint probability function P as follows:

$$P(X_1; ...; X_N) = \prod_{X_i \in X} P(X_n|X_1; ...; X_{n-1}) = \prod_{X_i \in X} P(X|P_{aG}(X)) \tag{1.5}$$

Nodes in the set of variable X are connected from P_{aG} to X where P_{aG} denotes the set of ancestor[22] of X_i in the structural causal model G. Indeed, that represents the causal relationships between the variables in the set X. Moreover, in the case where the joint distribution function P is empty, a variable X_i is not cause by any variable in the set X. To sum up, the objective of the DAG approach is twofold. The first function computes a set of probability distributions after that the second function represents causal structure across variables. In other words, this approach produces dense graphs of joint probability distributions between random variables, represented by nodes and a set of edges that connect each pair of nodes. To obtain graphs and causal inference, the DAG methodology implements an objective algorithm under two assumptions underlying the probability relations among each node to causal inference *(i)* Causal Markov Condition, *(ii)* Faithfulness (Ayyagari et al., 2013; Pearl, 2009). First, the Causal Markov Conditions stipulates that for a variable X_1 and another variable X_2 that does not have a direct effect on X_1, then X_1 is probabilistically independent of X_2 conditional on the direct effect of X_1[23]. Finally, the Faithfulness assumption states that independence relations are not found accidentally but from the Causal Markov condition. Therefore, independence relations in the observational data that are not from the Causal Markov condition, then the causal model is unfaithful.

To assess causal relations of explanatory variables on innovation intensity, we applied

[22] Ancestors of a variable X_i consist to all variables that are connected to X_i by an edge whose purpose is the variable X_i.

[23] In Bayesian networks and graphical theory of probabilistic causation, the Causal Markov condition is equivalent to d-separation (Spirtes et al., 2000; Pearl, 2009).

the PC-algorithm proposed by Spirtes et al. (2000). The algorithm uses the correlation matrix reported in Table 2. In the first step, the PC-algorithm produces an undirected graph plotting connections between all variables, without imposing conditional independence relations. In the second step, the algorithm produces endogenously a causal ordering of relations among the variables, testing all conditional independence relations between the variables. Finally, each edge without zero-order conditional independence relations[24] is removed until finding the true causal structure. To compare our findings to our main specifications in Table 3, we state a prior knowledge of variables order that consists of state innovation measures as dependent variables. Concerning specifications (2) and (3), competition-increasing product market regulations are defined as our independent variables[25].

Figure 1.2 reports conditional independence relations from the PC-algorithm using the correlation matrix of our balanced sample of 525 country-year observations. Figure 1.2 shows that conditional independence relations at the 5 percent level of significance are similar whether we use R&D intensity or the natural logarithm of patents corrected to country size as dependent variables, suggesting the same set of direct and indirect effects according to the innovation input and output. In addition, Figure 1.2 shows that the business regulation indicator has a direct effect on R&D intensity and the number of patents granted. The bidirectional arrow between business and trade regulation indicators suggests that domestic and foreign competition regulations are causing each other. Finally, conditional independence relations show that relations between market regulations and control variables are multiples. However, our main focus is to identify the direct causal determinants among domestic and foreign competition. The causal relations from the DAG are consistent with specifications (1) and (2), but the DAG analysis allows us to distinguish the direct and indirect effects of competition-increasing product market regulation. The difference between regression specifications and DAG analysis is that the unique statistical significant direct cause of innovation intensity is domestic product-market competition while foreign product-market competition indirectly impacts innovation.

In addition to the causal relations identified in Figure 1.2, we can infer the conditional distribution of a direct cause. For that purpose, we use the *do-operator* developed by Pearl (1995). The *do-operator* consists of intervention in the structural causal model

[24] Conditional independence test is equivalent to the null hypothesis that exists no partial correlation between random variable X and Y conditional on a subset of variable Z.

[25] Note that we do not impose prior knowledge among our independent variables, thus a causal structure can arise among this set of independent variables.

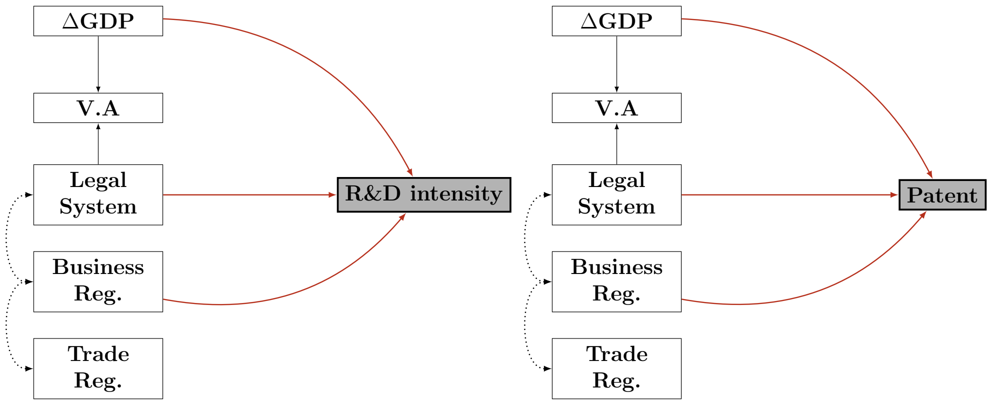


Figure 1.2 – Directed Acyclic Graph: Direct and Indirect Causal Effect of Competition at a five percent significance level.

obtained from our observational data represented in Figure 1.2.

A value x is fixed for X conditional on X=x'.

$$P(y|do(X = x)) = E(y|do(X = x^{"})) - E(y|do(X = x^{'})) \tag{1.6}$$

For each realization of x of X, the causal direct effect P(y|*do*(X=x)) assigns the probability y that is the post-intervention of distribution of outcome variable y. Specifically, the *do-operator* change the causal relations, removing each arrow going into X and substituting by a specific value X=x in remaining equation (Pearl, 2009; Imbens, 2019). Thus, we estimate the conditional distribution of business regulation on R&D intensity and the number of patents granted per capita as follows P(R&D intensity|*do*(Business Reg.=x)) and P(Patent|*do*(Business Reg.=x)). Using the *do-operator* suggests that the causal effect of product market regulation on R&D intensity is 0.440 and 0.360 for the number of patents granted per capita, and significant at the 5 percent level. The estimated causal effect of business regulation on innovation intensity appears similar to the coefficient for the FEVD and IV specifications (columns (4-6) of Table 1.3 and Panel A of Table 1.5)[26]. Consequently, lessen product market regulation increases the R&D intensity as well as the number of patents granted per capita at the country level.

[26]For example, the estimated causal effect of business regulation on R&D intensity through *do-operator* has a coefficient of 0.440 compared to 0.348 in the FEVD specification and 0.408 in the IV specification. Similarly, the causal effect of business regulation on the number of patents granted per capita has a coefficient of 0.360 compared to 0.782 in the FEVD specification and 0.304 in the IV specification.

5 Conclusion

This chapter aimed to examine the impact of competition-increasing product market regulation, summarized in domestic and foreign competition on innovation intensity in 25 OECD countries spanning 1995 to 2015. Our motivation is that the broad consensus on the importance of innovation for productivity growth contrasts with the long-lasting policy debate on the competition-enhancing product market interventions. We use novel empirical strategy and country-year level data on both innovation input (R&D expenditure) and output (patenting) to differentiate between the direct and indirect effects of competition on innovation. Our results show that product market regulation increasing domestic and foreign competition has a significant impact on innovation input as well as output. These results are robust to several alternative methods, addressing potential endogeneity issues through instrumental variable strategy, including lagged competition-enhancing regulation indicators as well as confounding factors.

Importantly, we highlight the source of competitive interactions. Using a graphical approach to causality, we prove that the positive response of innovation to competition in product markets was directly caused by regulation that increases domestic competition, while foreign competition is associated with the intensity of innovation through its indirect effect on domestic regulation that increases competition. Overall, our results suggest that increased competition in the domestic product market is effective in bringing about a significant increase in innovation in OECD countries.

Our results support Arrow (1962b)'s theoretical argument that competition in product markets encourages innovation through an escape effect. In terms of policy implications, reducing regulations that impede domestic competition in OECD countries could drive technological development through innovation activities. This chapter can be extended in several ways. First, it would be useful to examine the response of firms to competition regulation, using new firm-level data on innovation activities and market competition. This would allow us to explore in-depth the underlying mechanism that depends on the technological frontier and the reallocation process. Second, extending our analysis from OECD countries to other countries would be valuable.

Appendix

1.A Additionnal Information on Innovation Variables

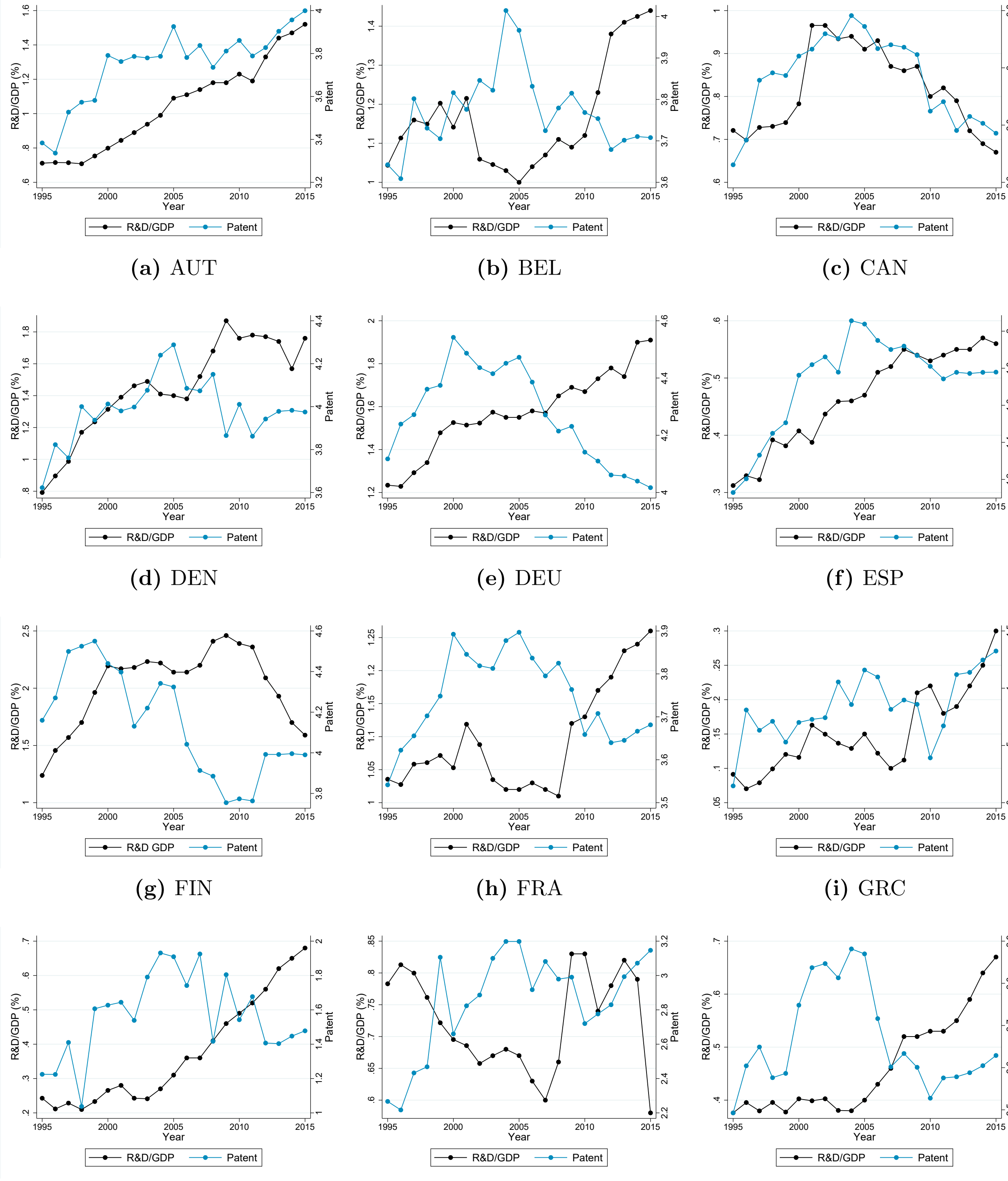
In this section, we provide additional information on innovation proxies used in our baseline identification strategy introduce in Section 3.1. In addition, Figure 1.A.1 presents innovation trends for each country included in our analysis sample over the period 1995-2015.

1.A.1 Innovation Definition

R&D Intensity. The R&D intensity measure used in our identification strategy comes from the OECD Science and Technology Indicators database. The variable is the ratio between R&D expenditure in the industry sector and the GDP, both in nominal values.

Patent. The Patent variable used in our identification strategy is the ratio between the number of triadic patents granted (i.e., EPO, JPO, and USPTO) and millions of inhabitants spanning 1995-2015 and transformed in logarithm.

1.A.2 Innovation Trends



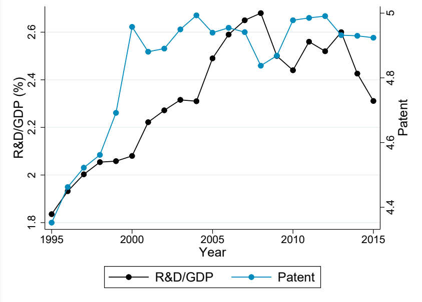
(a) AUT **(b)** BEL **(c)** CAN

(d) DEN **(e)** DEU **(f)** ESP

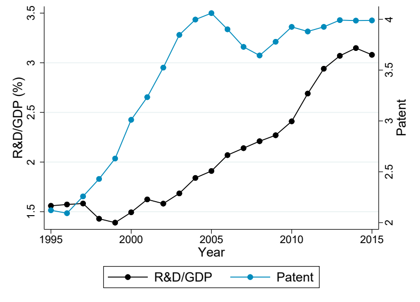
(g) FIN **(h)** FRA **(i)** GRC

(j) HUN **(k)** IRE **(l)** ITA

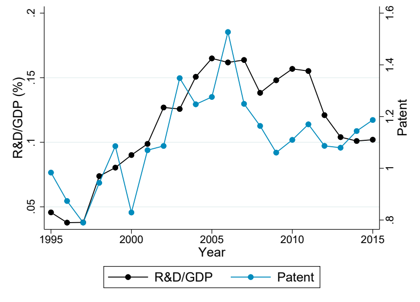
Figure 1.A.1 – Cross-country Innovation Trends: R&D intensity and Patent per capita.



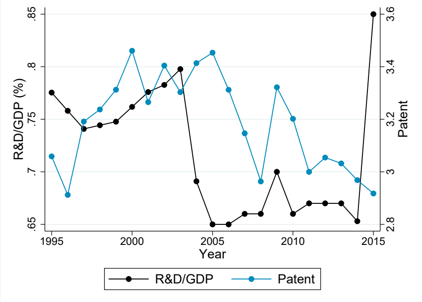
(m) JAP



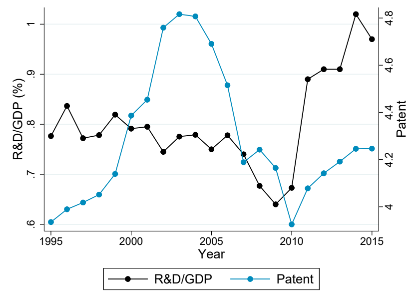
(n) KOR



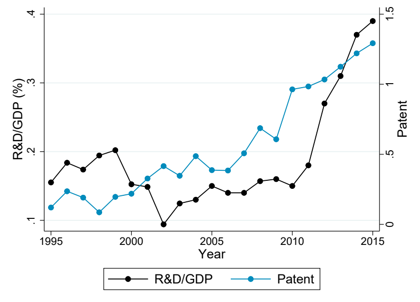
(o) MEX



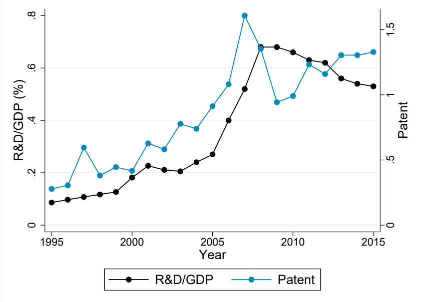
(p) NOR



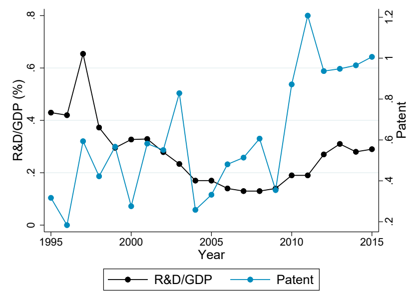
(q) NTH



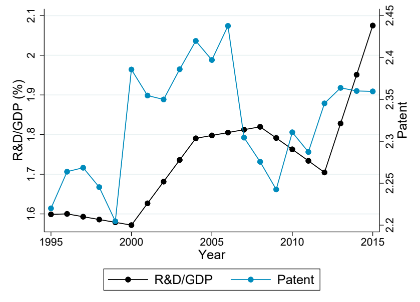
(r) POL



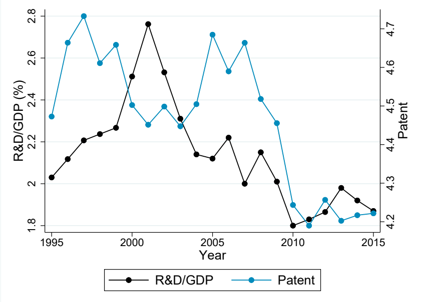
(s) PRT



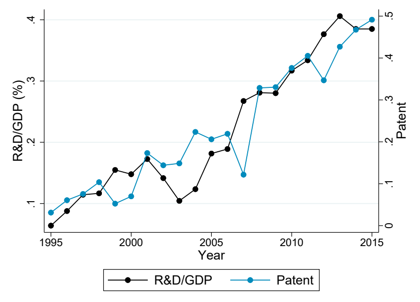
(t) SLK



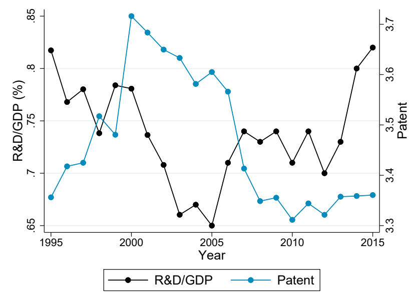
(u) SUI



(v) SWE

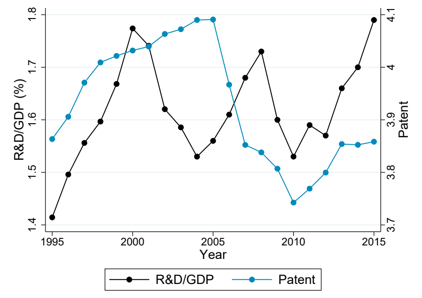


(w) TUR



(x) UK

Figure 1.A.1 – *(Continued)* Cross-country Innovation Trends: R&D intensity and Patent per capita.



(y) USA

Figure 1.A.1 – Cross-country Innovation Trends: R&D intensity and Patent per capita.

Notes: This figure shows the innovation intensity trends for each country included in our analysis sample spanning 1995-2015.

1.B Additional Information on Variables

In this section, we provide additional description of the control variable introduce in our main specification in Section 3.2.

1.B.1 Regulation Variables

Business Regulation. The Business Regulation Indicator (Business Reg.) is drawn from the Fraser Institute. The indicator measures the extent to which country business regulation impede entry by new firms and reduce competition among the market. The indicator is an average of six sub-indicators drawn from several databases: *(i)* Administrative requirements from the World Economic Forum, *(ii)* Bureaucracy costs from the IHS Markit, *(iii)* Starting a business from the World Bank's Doing Business, *(iv)* Extra payments/bribes/favoritism from the World Economic Forum, *(v)* Licensing restrictions from the World Bank's Doing Business, and *(vi)* Cost of tax compliance from the World Bank's Doing Business. As mentioned in Section 3.2, the indicator is on a scale of 0 to 10, with higher values indicating less stringent regulation.

Starting Business. The Starting Business Indicator is drawn from the Fraser Institute, but is based on the World Bank's Doing Business data that measure how it takes time and the cost to start a new business. Specifically, this indicator is an average of three sub-indicators: *(i)* time (measured in days) necessary to comply with regulations when starting a limited liability company, *(ii)* money costs of the fees paid to regulatory authorities measured as a share of per-capita income, and *(iii)* minimum capital requirements, that are funds that must be deposited into a company bank account measured as a share of per-capita income.

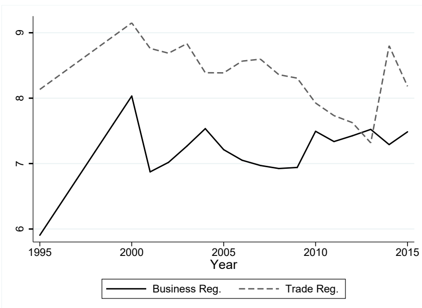
Bureaucracy Cost. The Bureaucracy Cost Indicator is drawn from the Fraser Institute, but is based on the "Regulatory Burden Risk Ratings" from IHS Markit, which measures "the risk that business operations become most costly due to the regulatory environment". The indicator is weighted according to sector contributions to GDP.

Trade Regulation. The Trade Regulation Indicator (Trade Reg.) is drawn from the Fraser Institute and measures how international trade is restrained by several determinants. The indicator is an average of nine sub-indicators drawn from several databases: *(i)* International Monetary Fund, *(ii)* World Trade Organization, *(iii)* World Economic Forum, *(iv)* World Bank Doing Business, *(v)* MRI Bankers' Guide to Foreign Currency, and *(vi)* Robert Lawson and Jayme Lemke (2012).

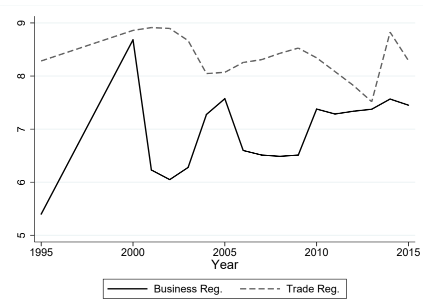
Tariff Barriers. The Tariff Barriers Indicator is drawn from the Fraser Institute and measure how international trade is restricted by tariffs. Specifically, this indicator is an average of three sub-indicators: *(i)* revenues from trade taxes, which measure the amount of tax on international trade as a share of exports and imports, *(ii)* mean tariff rate, and *(iii)* standard deviation of tariff rates, which measures whether tariff rates are uniform.

Non-Tariff Barriers. The Non-Tariff Barriers Indicator is drawn from the Fraser Institute, but is based on the World Economic Forum, Global Competitiveness report that measures how non-tariff barriers reduce the capacity to import goods and be competitive on the domestic market.

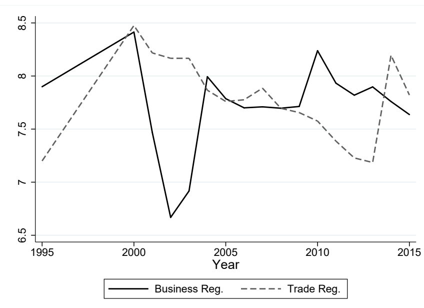
1.B.2 Regulation Trends



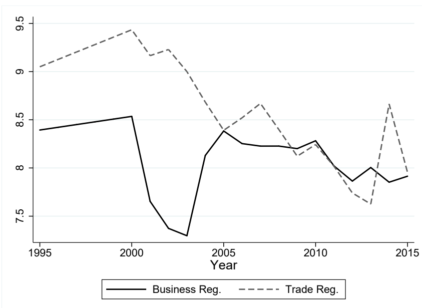
(a) AUT



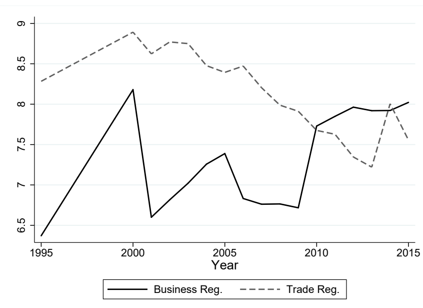
(b) BEL



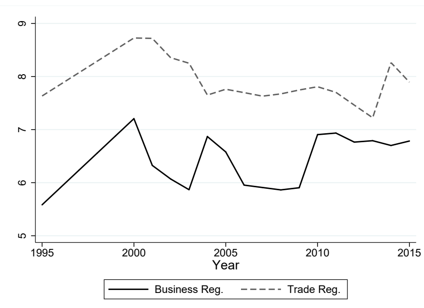
(c) CAN



(d) DEN

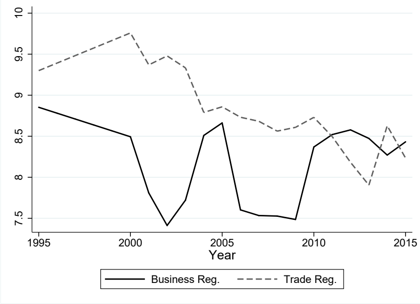


(e) DEU

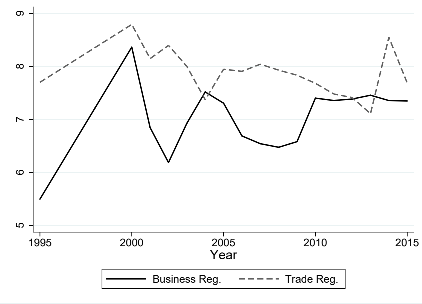


(f) ESP

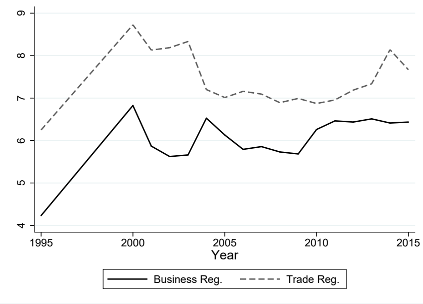
Figure 1.B.1 – Cross-country Regulation Trends: Business and Trade Regulation Indicators.



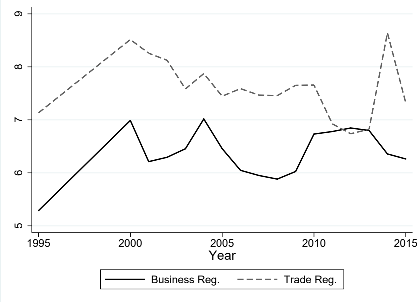
(g) FIN



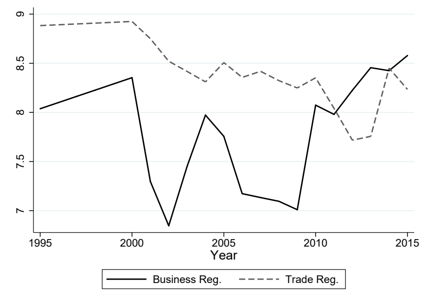
(h) FRA



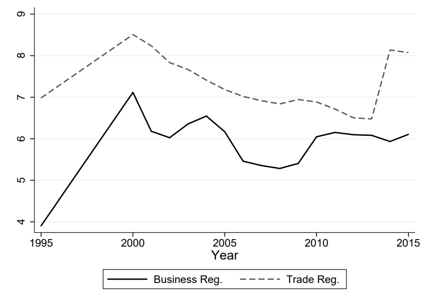
(i) GRC



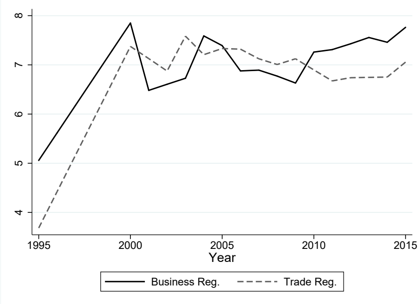
(j) HUN



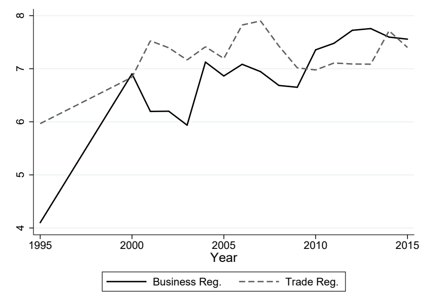
(k) IRE



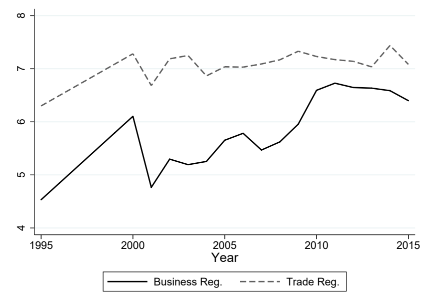
(l) ITA



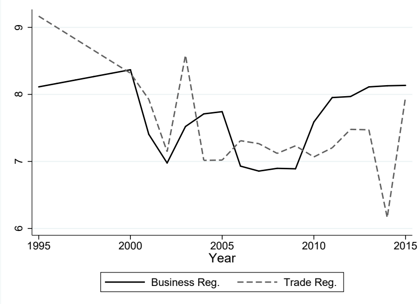
(m) JAP



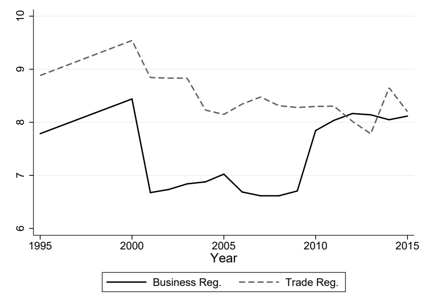
(n) KOR



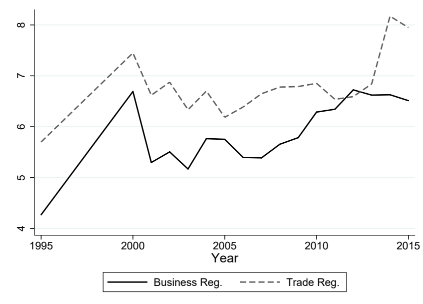
(o) MEX



(p) NOR

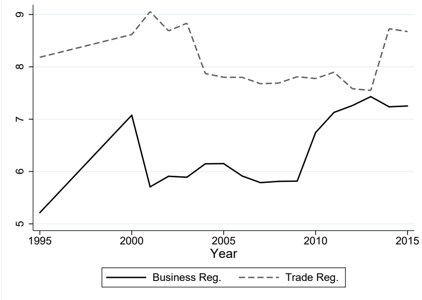


(q) NTH

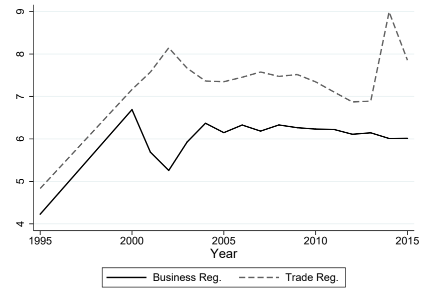


(r) POL

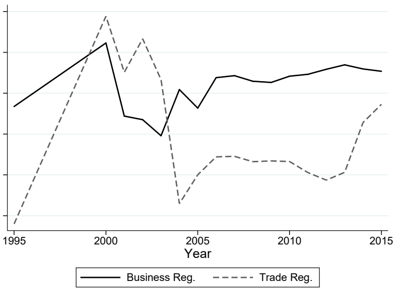
Figure 1.B.1 – *(Continued)* Cross-country Regulation Trends: Business and Trade Regulation Indicators.



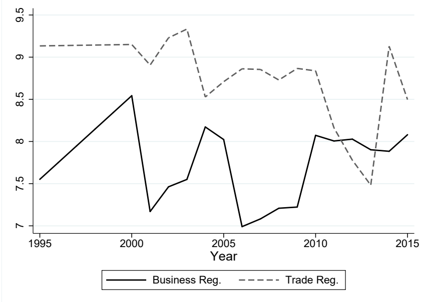
(s) PRT



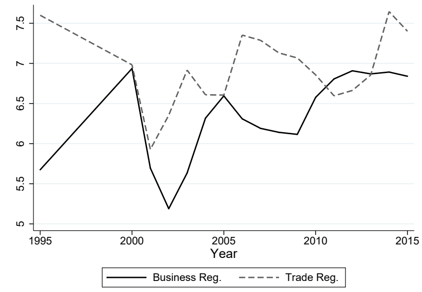
(t) SLK



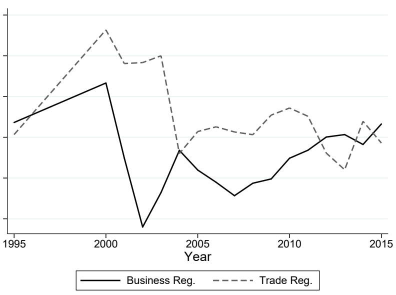
(u) SUI



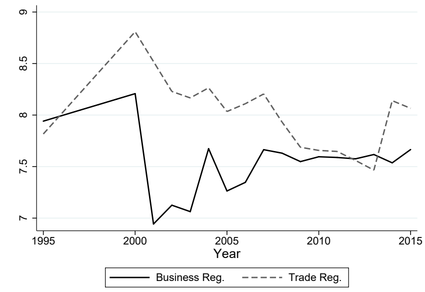
(v) SWE



(w) TUR



(x) UK



(y) USA

Figure 1.B.1 – *(Continued)* Cross-country Regulation Trends: Business and Trade Regulation Indicators.

Notes: This figure shows the regulation trends for each country included in our analysis sample spanning 1995-2015.

1.B.3 Additionnal Variables

GDP Growth. We measure the growth rate by the annual percentage growth rate of GDP at market prices based on constant local currency. The measure is expressed in constant 2010 U.S. dollars.

Value Added. The value-added measure is the ratio between the net output of the manufacturing sector (i.e., ISIC divisions 15-37) and the GDP measured at purchaser prices.

Legal Integrity. The Legal Integrity Indicator is drawn from the Fraser Institute. We use an aggregate index, which aggregates information on variables measuring judiciary independence, the impartiality of the courts, protection of intellectual property, law and order, and legal enforcement of contracts. These indexes, just like the WGIs, are based on the perceptions of enterprisers, citizens, and experts. The indicator is on a scale of 0 and 10, with higher values indicating better governance outcomes.

Import Penetration Ratio. We use the importation penetration ratio as the ratio between the value of imports as the percentage of total domestic demand, where the total domestic demand for country i is defined as follows:

$$D_{it} = (Y_{it} - X_{it} + M_{it}) \tag{1.7}$$

where Y_{it} is the country's output, X_{it} country's export, and M_{it} country's import measured in million USD. Data are drawn from the OECD Trade Indicators.

Foreign R&D. Foreign R&D Stock in the manufacturing sector was calculated following the framework proposed by Coe and Helpman (1995) using the domestic R&D capital stock of the country's trade partners included in the panel.
Foreign R&D stock is defined as follows:

$$S_i^f = \sum_{j \neq i} w_{ij} S_j^d \tag{1.8}$$

where w_{ij} denotes the country's imports of goods and services from trade partners. Bilateral-import-share is drawn from the IMF Trade Database and is expressed in C.I.F basis.

1.C Instrumental Variable Strategy

To address the endogeneity issues and test the robustness of our baseline results, we propose an alternative identification strategy using an instrumental variable (IV) approach. A first concern is those regulation indicators might reflect endogenous regulatory changes to innovation during the analysis period. Second, those regulation indicators might be correlated with unobserved country characteristics that are correlated with innovation intensity. To address this identification challenge, we estimate specification (1.1) using an instrumental variable strategy, where we instrument for the business and trade regulation indicators with the average of these indicators in other jurisdictions. Specifically, we split jurisdictions between European and non-European countries. The first and second stages of our identification strategy are given by:

$$Reg_{ct} = \alpha_0 + \alpha_1 AverageReg_{ct} + \alpha_2 X_{ct} + u_c + u_t + \varepsilon_{ct} \tag{1.9}$$

and

$$y_{ct} = \beta_0 + \beta_1 \widehat{Reg_{ct}} + \beta_2 X_{ct} + u_c + u_t + \varepsilon_{ct} \tag{1.10}$$

where $\widehat{Reg_{ct}}$ is the predicted regulation indicators. We allow the instrument to change across years in order to capture regulatory changes that evolved over time. Therefore, our estimates of β_1 are identified only by variation in regulatory changes in other jurisdictions, that are not correlated with innovation intensity in a specific country.

Appendix Table 1.C.1 reports first stage regressions that correspond to results reported in Table 1.5.

Table 1.C.1 – First-Stage Regressions.

	Business Reg. **(1)**	Trade Reg. **(2)**
Average Business Reg.	1.037***	
	(0.174)	
Average Trade Reg.		0.949***
		(0.165)
Kleibergen-Paap Wald F-statistic	35.49	33.01
Country Effects	Yes	Yes
Time Effects	Yes	Yes
Obs.	525	525

Notes: This table presents first-stage regressions of our instrumental variable strategy. In column (1), the dependent variable is the business regulation indicator instrumented with the average of business regulation on other jurisdictions. In column (2), the dependent variable is the trade regulation indicator instrumented with the average of trade regulation on other jurisdictions. Robust standard errors in parentheses. *** p<0.01.

Chapter 2

Innovation Performance and the Signal Effect: Evidence from a European Program

---

This chapter was co-authored with **Nadine Levratto**.

Summary of the Chapter

This chapter seeks to estimate the effect of a European policy that subsidizes innovation investments. By carefully selecting observables, we compare recipients of the program with non-recipient firms to overcome the endogeneity of R&D grants. We conduct a difference-in-differences design on the universe of a unique firm-level dataset of European SMEs between 2008 and 2017. We find a significant effect of proof of concept grants, which implies an increase in the number of patent applications and the probability of patenting. There are positive impacts on credit financing, which suggest a signal effect to investors about the project quality of young firms.

Classification

JEL Classification: G28, G32, O30, O38.

Keywords: R&D subsidies, Innovation, Patent, Financing constraints, H2020.

Acknowledgments for this chapter

The authors would like to thank Bettina Peters, Maikel Pellens, Benjamin Monnery, Ilia Samarin, Julien Salin, and seminar and conference participants at the 8th ZEW/MaCCI Conference on the Economics of Innovation and Patenting in Mannheim, the Competition and Innovation summer school in Ulcinj, JRC Concordi 2019, and Paris Nanterre University (EconomiX) for helpful comments.

Contents of the Chapter

1 Introduction

Public support for private research and development (R&D) investments and breakthrough innovations have gained popularity among developed and emerging countries through tax incentives and direct subsidies[1]. The theoretical rationales for R&D subsidies are that firms cannot internalize the social return to R&D, which leads to a suboptimal resource allocation of private R&D. Another rationale is that R&D investments face financial constraints reinforced by informational asymmetries and project uncertainty. Despite the establishment of R&D subsidies and their popularity in industrialized economies[2], the causal evidence on patenting activities is quite ambiguous, scarce and uninformative regarding the crowd-in or crowd-out effect on private investments. This ambiguity raises a major policy issue regarding whether such schemes are effective for improving innovation propensity.

A central concern is that these direct subsidies from selective programs might induce inframarginal investments that would have been undertaken without public support. Consequently, the additionality effect of direct R&D subsidies is determined by the public agency selection of program winners and monitoring. Another concern in the empirical literature on R&D subsidies is the absence of exogenous variation to policy intervention and the selection bias caused by the non-randomness of treatment assignment. In this context, treated and control groups might differ both in observable and unobservable characteristics that lead to endogeneity issues, which amplifies the difficulty in assessing the effectiveness of public support (Cerqua and Pellegrini, 2014; Neumark and Simpson, 2015).

We overcome the potential selection bias by using robust propensity score-matching to capture observable characteristics that determine R&D grant allocation. More specifically, during our sample period spanning 2008-2017, we examine the effect of R&D grants implemented in 2014 under the Horizon 2020 program, the Small-and Medium-sized Instrument (SMEI) on both the number of patent applications and the likelihood of patenting. This program is similar to the Small Business Innovation Research (SBIR) in which federal agencies provide R&D subsidies for high-tech ventures (Lerner, 2000; Howell, 2017). The SMEI Program comprises two distinct phases. Phase 1 supports feasibility and proof of concept projects with a grant of €50,000, whereas Phase 2

[1]For example, the United States has implemented the Small Business Innovation Research program, Israel's Chief Scientist incubator program, the ITW in Flanders, the Business Basics Fund in the United Kingdom.

[2]In 2017, total public support for private R&D accounts for 0.64 percent of European GDP, which corresponds to €98 billion. Note that this public support was constant over the period 2008-2017.

winners receive a grant that ranges between €500,000 to €2.5 M to fund the readiness to market of breakthrough innovations. Applicants are selected on project quality through exogenous European cut-off dates. At each cut-off, innovative projects are ranked by independent experts who give an overall score, and the highest-ranking scores are selected as the program winners according to the planned budget. The selection process examines the observable characteristics of the winning firms before and after the policy intervention using a unique set of data merged with the balance sheets of the program's winning firms as well as a randomly selected sample of innovative European firms. The causal effect of R&D grants on the firm-level patent count and the probability of patenting is identified in a difference-in-differences (DID) specification with a matched counterfactual group of firms that have similar pre-policy intervention observable characteristics but that did not receive a grant from the European program.

Our main finding suggests that R&D grant assignment to Phase 1 winners has a positive and statistically significant effect on innovation propensity. We show that R&D grants increase the intensive response for recipient firms by approximately 1.4 times with respect to non-recipient firms and by 1.6 times for the extensive response. Within three years after the grant assignment, the effect continuously increases. By contrast, our main estimates suggest that R&D grants in Phase 2 have no significant effect at both the intensive and extensive margins. Therefore, the proof of concept grant has an additionality effect on the patenting of firms, which enables recipient firms to experiment and develop new inventions. In addition, we explore the treatment heterogeneity with respect to the age and size of firms as proxies of ex-ante financial constraints. We find that younger firms (i.e., under 8 years old) are substantially more inclined to respond positively to R&D grants than their counterparts. According to our preferred conditional difference-in-differences for the Phase 1 winners, we provide a back-of-envelope calculation of the direct cost-per-patent. We find a direct cost-per-patent in the range of €94,000 to €146,000. Finally, we show that the innovation propensity effect of the R&D grant can be partially explained by the positive effects of the outstanding debt of younger firms. The results shed more light on the role of financial constraints and the role of the grant as a signal effect on investors.

The main limitation of our quasi-experimental design is that the program might be correlated with unobservable shocks that confound the patenting response. We address this concern in several ways. First, in an event-study design, we show graphically and statistically that there is no differential trend in the treated and control group in the pre-intervention period. Second, we implement a series of placebo tests that suggest that our results are not affected by a false assignment year and placebo treatment status. Third, we control for the potential anticipation effect of the subsidy assignment and show that our results are due to the R&D grant and not to an Ashenfelter Dip effect (i.e., a reduction in patent applications in the year preceding grant reception followed by an artificial increase in the post-intervention period). Finally, the point estimates are robust to alternative specifications and fixed effects.

This chapter is related to several strands of the literature. First, our chapter contributes to the large literature on public incentives and effectiveness on R&D investments and innovation, which refers to the most important policymakers' concerns. Although an increasing body of work examines the role of fiscal incentives on physical and R&D investments (Guceri and Liu, 2019; Ohrn, 2018; Rao, 2016; Yagan, 2015; Zwick and Mahon, 2017), the evidence on R&D grants are inconclusive. Moreover, there is little evidence regarding the effectiveness of such public support on innovation output. Our findings have important implications. First, we estimate the effect of the European program on the initial cutoff in 2014. Thus, our results shed light on similar program design to the U.S SBIR but on a different institutional environment, which improves policy recommendations in the European context. Finally, instead of using a small sample of small high-tech firms (e.g., Lerner 2000 and Howell 2017), we use a unique, and unexploited set of small-and-medium-enterprises (SMEs) that covers a large diversity of technological sectors. This enables us to improve the importance of our results and show the treatment heterogeneity in the program, which could be hidden by a comparison of treated and untreated firms located around a threshold.

Second, our chapter adds to a broader literature on supportive business schemes and place-based policies in developed countries. The nascent literature has evaluated the causal effect of place-based support on capital and investments in European countries (Becker et al., 2013; Criscuolo et al., 2019; Hünermund and Czarnitzki, 2019; Bronzini and de Blasio, 2006). Despite the additionality effect of place-based programs on investments and the treatment heterogeneity among areas, they remain an important research question for future works.

Finally, this chapter relates to a broader literature on financing constraints in the presence of imperfect capital markets, in particular on the role of public grants in signaling project quality to early-stage investors (Lerner, 2000; Howell, 2017; Meuleman and De Maeseneire, 2012). Most studies have focused on public firms, and evidence on whether public support for SMEs shifts downward the user cost of capital are sparse.

This chapter provides evidence that early-stage R&D grants signal private information.

The remainder of the chapter is organized as follows. Section 2 discusses the theoretical rationale and related literature; Section 3 describes the program and selection process in detail; in Section 4, we describe the data and sample construction; we present the identification strategy in Section 5 and, report our main results for Phases 1 and 2 as well as robustness tests; Section 6 explores potential mechanisms; Section 7 provides the magnitudes of the estimated treatment effect, finally Section 8 concludes.

2 R&D Grants and Innovation Propensity: Related Literature

In the public policy literature, public support for private R& D has the ambition to increase private R&D effort, technology capability, and competitiveness. In theory, R&D incentives (i.e., grants, loans, and equity-based instruments) to private firms are justified to address two market failures. First, according to the innovation literature, and particularly the argument developed by Nelson (1959) and Arrow (1962b), R&D investments generate positive externalities, owing to the good public nature of knowledge. Thus, other firms have the opportunity to take advantage of R&D activities previously carried out to develop new inventions, imitate innovations at a lower cost, to market new products to gain the lead over its competitors (Hall et al., 2010). Therefore, knowledge externalities or positive spillovers cause incomplete appropriability of returns to R&D activities leading to lower innovative investments from the private sector than the optimal social level. In addition, as argued by Mansfield et al. (1977) and Lerner (2000), problems related to the public nature of knowledge are more severe for small firms, suggesting that R&D programs dedicated to SMEs can be appropriate to enhance R&D investments.

The second theoretical argument is based on capital market imperfections due to information frictions, increasing the cost of external capital. These information frictions are due to information asymmetries between inventors and external investors, such as banks, private equity, or venture capitalists (Hall et al., 2010). Innovative investments are riskier than traditional investments and very uncertain, and managers are better informed about the quality of the project and its chances of success (Myers and Majluf, 1984; Stiglitz and Weiss, 1981). Overall, this information gap increases the difficulty of external investors to evaluate an innovative project. These problems are particularly severe for young, startups, and SMEs (Hall et al., 2010). Consequently, it is commonly recognized that SMEs have more difficulties in raising external capital, and these financial constraints seriously hamper their R&D and innovative activities (Carpenter and Petersen, 2002; Himmelberg and Petersen, 1994). Finally, it is argued that it is more tricky to finance intangible capital[3] because firms do not have sufficient collateral to pledge[4] unlike firms with a higher proportion of tangible assets (Hall et al., 2010). This market failure can lead to difficulty in raising external capital and could hinder the innovative project of financially constrained firms. Therefore public grants following a selective scheme could alleviate this second market failure by providing additional funds and reducing information asymmetries (Colombo et al., 2011).

In theory, public policies subsidizing private research (i.e. based on selective schemes) are effective to support recipient firms by increasing investments, also called "additionality effect", contrary to the "crowding-out effect". The additional effect occurs for projects that would not be launched without the grant because of an excessive cost relative to expected returns (Bronzini and Iachini, 2014). In this case, subsidies could transform projects into profitable investment opportunities, reducing information frictions and financial constraints. One potential mechanism could be a certification effect for selective schemes, increasing quality assessment for external investors (Lerner, 2000; Lanahan and Armanios, 2018)[5]. In contrast, the crowding-out effect occurs for innovative projects with positive net present value without subsidies. In this case, the firm does not invest in additional R&D projects and there is a substitution between private financing for a less costly public solution (Wallsten, 2000; Lerner, 2000). These opposing effects justify the evaluation of R&D grants for innovative SMEs, particularly since the budgetary pressure on the public budget of developed countries make it necessary to assess whether these instruments are well-targeted towards the most promising firms.

There is a large strand of the literature that examines the effect of R&D grants on the dynamic and R&D investments of firms, but provides mixed-conclusions. In a survey of microeconomics studies, David et al. (2000) review 33 empirical papers, mainly in the U.S, and covering 35 years of findings before 2000. Overall, the authors conclude that 11 studies support the crowding-out effect of public support. In contrast, a recent survey provided by Becker (2015) sheds light on the positive incentive on R&D activities and

[3]For example, in a recent literature review on the financing of innovation, Hall et al. (2010) argued that the knowledge base of innovative firms represents fifty percent of wages and salaries of human capital. It is, therefore, a knowledge incorporated in the human capital of the firm that cannot serve as a guarantee.

[4]Nascent empirical literature suggests the role of patents as collateral for debt financing (Hochberg et al., 2018; Mann, 2018). For example, Mann (2018) shows that 38% of patenting firms in the US to pledged patents as collateral to raise additional debt financing.

[5]An alternative mechanism is that selective programs based on an evaluation process could have a learning effect, especially for young and small firms compared to incumbents. This effect could increase the application rate and success (Hottenrott and Demeulemeester, 2017; Zúñiga-Vicente et al., 2014).

an additionality effect on recipient firms, more pronounced for small firms. However, this controversial evidence is due to selection bias and endogeneity issues. Selective schemes such as R&D grants involve scrutiny of the project quality, firms' characteristics, therefore recipient firms are not selected randomly and differ from their counterparts (i.e. non-recipient firms). The non-randomness decision of participation and access to confidential data from government agencies raised challenges to identify causal effects (Zhao and Ziedonis, 2020; Bronzini and Piselli, 2016), involving the importance to address this selection bias into the econometric specification (David et al., 2000; Jaffe, 2002)[6].

Despite this voluminous empirical evidence, the effectiveness of R&D grants to stimulate patent filing and citations are sparse (Bronzini and Piselli, 2016; Le and Jaffe, 2017)[7]. By using propensity score matching (PSM) and Heckman selection model to evaluate the effect of the Chinese program dedicated to innovative SMEs, Guo et al. (2016) report the positive influence of public support on new outputs, in terms of sales of new products and patent filing compared to non-recipient firms. With an alternative approach, namely regression discontinuity design (RDD) and on regional Italian R&D program, Bronzini and Piselli (2016) document a similar relationship between subsidies and patenting activities. With similar methodology but on the effectiveness of the SBIR program, Howell (2017) confirms the positive effect on cite-weighted patents generated by US startups. In contrast Moretti and Wilson (2014) provide controversy findings on patent filing. The authors examine the effect of state-based public subsidies programs on US firms operating in the biotechnology sector and do not find a large impact on patent filing at the state level.

Whether and how subsidy directly reduces market frictions is theoretically ambiguous, existing evidence on the impact of selective programs on financing constraints and external sources of financing for startups and SMEs are still limited (Lerner, 2000; Howell, 2017). Lerner (2000) compares startups that received an R&D subsidy from the Small Business Innovation Research (SBIR) program in the US to non-recipient startups. Using matching methodology, Lerner (2000) highlights that recipient firms are more likely to attract venture capital. More importantly, he points out the underlying mechanism. In fact, selective programs could provide a signaling effect (i.e. "certification effect") that reduces informational frictions for external capital providers. Meuleman and

[6]In light of this challenge, a growing literature relies on the advantage of proposal scores for recipient and non-recipients firms using regression discontinuity design to estimate the local average treatment effect. See Howell (2017), Bronzini and Iachini (2014), Bronzini and Piselli (2016), and Wang et al. (2017).

[7]Empirical analysis mostly encompasses evidence on innovative inputs, including Guceri and Liu (2019), Colombo et al. (2011), Czarnitzki and Lopes-Bento (2014), Bronzini and Iachini (2014), Lach (2002), Wallsten (2000), Görg et al. (2008), and Hünermund and Czarnitzki (2019).

De Maeseneire (2012), based on panel fixed logit methodology and on a sample of Belgium SMEs, document a positive relationship between R&D grants and subsequent access to long-term debt financing and private equity, supporting the hypothesis of certification effect. Similarly, Hottenrott et al. (2017) examines a sample of Belgian startups and tend to find a significant effect of R&D subsidies on the likelihood to access debt financing. However, this positive effect is limited for startups in the technology-intensive sector, while it is insignificant for low-tech firms, suggesting a more pronounced effect in the uncertain and opaque environment. Takalo and Tanayama (2010) argue from a theoretical framework that selective subsidies provide an information source to outside investors on the evaluated project by public agencies. Nevertheless, this positive signal is based on the reputation of the public agency and the governance (Guo et al., 2016; Bronzini and Iachini, 2014). In contrast, Howell (2017) argues that the increase in innovative output and subsequent VC financing is due to a resource effect rather than a certification effect.

In sum, empirical evidence on the effectiveness of public support on the innovation propensity of firms is mixed and limited to state and local innovation policies. Our chapter contributes and extends the existing literature on innovation outputs. First, we provide new evidence based on a European program (i.e., H2020) for innovation and market-solutions. Our analysis sample is particularly helpful for policy evaluation. To reach the objective of R&D investments of 3% of GDP, several European policies were implemented. However, competitiveness in science and technology has declined compared to the U.S and China, involving a new program set to attract new actors, such as SMEs. Second, we examine small-and medium-sized firms. These features allow us to differentiate the grant effects by firm characteristics in the European context. Finally, we contribute to the underlying mechanism of the quality signal, which is frequently neglected for program evaluation analysis.

3 Institutional Framework: The SME Instrument

3.1 *Program Overview*

The SME Instrument is a selective public program for European startups and SMEs. It is a joint initiative of the European Innovation Council (EIC) and the European Commission (EC). This program is a part of the eighth Horizon 2020 Framework Program[8], which was adopted on December 10, 2013 by the EC and formally launched

[8]European Union has started to focus on research and innovation excellence by introducing structural framework as early as 1982. The first European research agenda, namely Framework Programme (FP1) dedicated to science and technology excellence was introduced in 1984 covering three years (1984-1987).

in 2014. The formal objective of the SMEI is to support innovation and close-to-market activities, which therefore improves job creation and productivity growth in Europe.

The program provides financial support, coaching and networking to SMEs with high-growth potential opportunity and marketable inventions in existing sectors and new markets. The first cut-off occurred in June 2014 and extends until November 2017[9]. Of the 3,208 program winners from a total of 46,772 program applicants across the 33 involved countries[10], around €1.31 billion was granted whose €250 million in 2014.

3.2 *Eligibility and Selection Process*

The SMEI is mainly designed on the largest R&D subsidies program that occurs in the US, namely, the Small Business Innovation Research Program (SBIR), and comprises three independent phases. Figure 2.1 presents a schematic of the SMEI program steps, which are described and summarized in this section.

Phase 1 corresponds to a phase of the proof of concept and accesses the feasibility of the innovative idea. The final objective of Phase 1 is to provide a robust business plan that considers the innovativeness and risks of the project. Phase 1 grants a unique lump sum of €50,000. The duration of the investment is 6 months and can lead the recipient firm to apply for the second phase of the program. Phase 2 corresponds to the forward step where SMEs are focused on R&D activities, prototyping, and demonstration and is aimed at inducing innovation and commercialization. The grant awarded ranges from €500,000 to €2.5 million per project. For both phases, the subsidy covers 70 percent of the total investment cost planned. The duration of the investment can largely be extended relative to Phase 1 and ranges from 1 to 2 years. Finally, Phase 3 is an acceleration process to strengthen innovation commercialization. However, only a small portion of SMEs (1 percent) access this final step. Therefore, we exclude this phase from our evaluation analysis to focus only on the first two phases of the SMEI program.

The SMEI program is based on a competitive scheme so that projects are granted after a selection and evaluation process. Indeed, applicants submit a business plan that

[9]The SMEI program runs until 2020, with an average of 8 cut-offs per year. Our analysis uses the first year of the program, which allows us to cover the short-term effect.

[10]Countries under the SME instrument included: Austria, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Latvia, Lithuania, Luxembourg, Macedonia, Malta, Moldova, Netherlands, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Turkey, the United Kingdom.

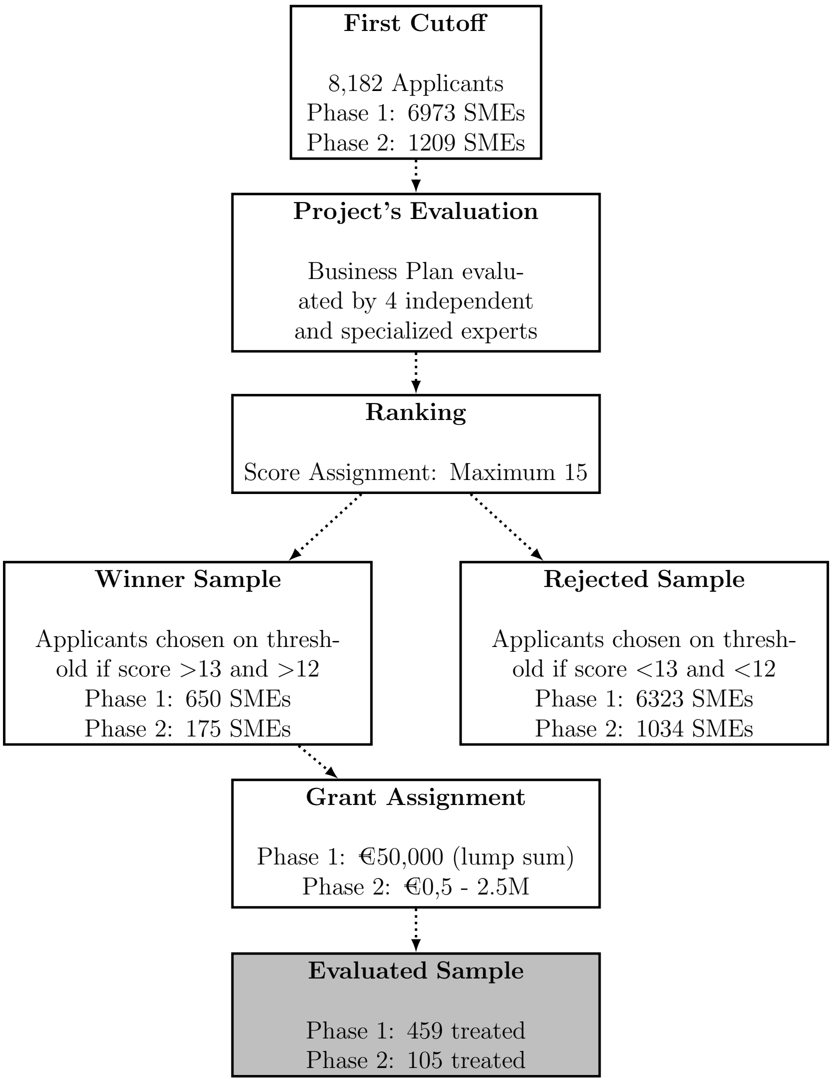


Figure 2.1 – Program Stages and Timing of the Investment.

Note: This figure shows the program steps in the first cut-off year (2014) and R&D grant assignment for chosen innovative projects.

will be evaluated by four independent and specialized experts at the national level. The submitted business plan is scored on the three distinct criteria of *(i)* impact, *(ii)* excellence and *(iii)* the quality and efficiency of the implementation with a score that ranges between 0 and 5 for each criterion, which gives a maximum score of 15 for a proposal[11]. The program is selective because R&D grants are awarded conditionally up to a threshold value, and only the highest-ranking projects are selected at each cutoff. For Phase 1, the overall threshold is 13 with a minimum value of 4 per criterion. In contrast, in Phase 2, the overall threshold is 12 with a minimum of 4 for the impact criterion and 3 for the remaining two criteria. This selection process ensures that the

[11]The overall score is based on the median score given by each evaluator.

highest-ranking business plans on innovation potential are selected.

Panel B of Table 2.1 summarizes the treatment group for our analysis sample of program winners in the first cutoff[12] (2014) from ten European countries. This gives a total of 651 program winners divided between 459 and 105 firms in Phases 1 and 2, respectively.

Table 2.1 – SME Instrument Proposal Distribution

	Total SMEI	**Phase 1**	**Phase 2**
Panel A: Overall sample			
Proposal evaluated	8182	6973	1209
Recipient projects	825	650	175
Non-recipient projects	7357	6323	1034
Successful rate	10.1%	9.3%	14.4%
Panel B: Evaluated sample*			
Proposal evaluated	5350	4498	852
Recipient projects	651	459	105
Non-recipient projects	4699	4039	660
Successful rate	14.9%	10.2%	12.3%

Notes: This table presents in Panel A the overall proposals received by the European agency EASME in 2014 among countries included in the program. * Panel B presents the distribution of program winners on our evaluated sample of countries: DE, ES, FI, FR, IR, IT, NL, NO, SE, UK.

4 Data and Summary Statistics

4.1 *Sample Selection*

We combine five distinct datasets to construct our main analysis sample of innovative firms. In particular, we match the Executive Agency for SMEs (EASME) data with the Bureau Van Dijk's Amadeus dataset, PATSTAT, and Crunchbase, which was completed with Dealroom. The resulting sample is an unbalanced panel of the population of the SMEI program's winners and European innovative firms, which consists of 454,247 firm-year observations spanning 2008 to 2017.

The EASME is the administrative database provided by the European Commission (EC)[13] and is used to supervise Horizon 2020 projects. The database contains information

[12]In 2014, a total of 4 cut-offs was introduced. The distribution of the cut-off dates was as follows, the first cut-off date was in June 2014, the second in September 2014, the third in October 2014 and the last deadline was in December 2014. However, only two cut-off dates were available for applicants firms to Phase 2 (October and December).

[13]According to Article 35(3) of the Financial Regulation (Regulation EU, Euratom No 966/2012 of the

on all program winners since 2014 and provides detailed information on the identifier and address of firms, a short project description, the objective, the amount applied for, the amount of the R&D grant, and the participation phase. The EASME allows identifying recipient firms and dividing the analysis between the proof of concept (Phase 1) and development and commercialization (Phase 2) phases but not the firm characteristics (i.e., balance-sheet information). Therefore, we match the program winners with the data from Amadeus that contains all European balance sheet information reports to tax authorities or data collection agencies[14]. This allows us to merge over 86 percent of all the SMEI program winners from which we can merge 63 percent of balance-sheet information after cleaning, which covers the period from 2008 to 2017. Non-matched firms are mostly due to a lack of available information on the analysis period in Amadeus[15]. The resulting sample, which refers to treated firms, includes 4,110 firm-year observations for 3,310 and 870 firm-year observations that belong in Phases 1 and 2, respectively.

The main control group used in this chapter comprises European SMEs that never experienced the treatment (i.e., R&D grants from the SMEI program) (Borusyak and Jaravel, 2017; Freyaldenhoven et al., 2019). Specifically, from Amadeus, we have randomly drawn a sample of SMEs localized in the ten European countries that our analysis covers from the entire firm population and from merged balance sheet information. We select our control group on the following criteria. First, the SMEI program eligibility rules involve firms with a number of employees of less than 250 and a turnover and a balance sheet inferior to €50 M and €43 M, respectively. Second, the SMEI program involves firms that exhibit a high potential for innovation and growth, with breakthrough ideas and close-to-market innovation. Therefore, a firm is identified as innovative if it has an invention patented in one jurisdiction[16]. The resulting sample, which refers to the potential control group, consists of 432,470 firm-year observations from 2008 to 2017.

European Parliament), publication of information on value and recipients of Union funds is limited to program winners. Hence, we are unable to implement an experimental framework because the EASME database does not provide information on the overall sample of applicants firms. Additionally, we do not observe the score-based assignment of the public program and the threshold around the cut-off, that, for example, allows us to implement RDD design (Bronzini and Iachini, 2014; Bronzini and Piselli, 2016; Howell, 2017).

[14]We regard unconsolidated balance-sheets to avoid problems of data manipulation between subsidiaries and head firms, which might lead to biased estimates.

[15]This match-rate of all recipient firms is highly similar than the matching rate (68 percent) of Santoleri et al. (2020) that use private data on firm-applications from the EASME. The authors compute standardized mean differences between the population of applicant firms and the Amadeus-matched sample and find no statistically significant differences among the two groups, which is reassuringly. Also, Bureau Van Dijk does not provide an optimal coverage of younger and smaller firms information on balance-sheet.

[16]Defining innovative capacity through patent measures may seem restrictive because not all firms that file patents make R&D investments, but there are inventions without R&D.

PATSTAT is a database that provides information on the patent applications granted in all worldwide jurisdictions. The raw dataset holds 15 million patents filed at major offices such as the European Patent Office (EPO), the United States Patent and Trademark Office (USPTO), the Japan Patent Office (JPO) and the applications filed via the Patent Cooperation Treaty (PCT) at the World Intellectual Property Organization (WIPO) from 1978 to today. However, we restrict our analysis until 2017, which allows a sufficient time period to examine the short time effect of R&D grants on patenting. To achieve our final panel of the treated and control groups, we match patents to European firms based on the firm name and the accounts for name changes. We also use the matching operation between PATSTAT and Amadeus to avoid missing patent assignments, and we check the matching quality manually.

Finally, we complement the SMEI program winners, balance sheets, and patent information with private financing events from Amadeus, Crunchbase and Dealroom. These databases contain information on the total outstanding debt divided between short- and long-term outstanding debt. In addition, Crunchbase and Dealroom provide information on the public subsidies received from other European-based programs that are dedicated to innovation at SMEs[17].

4.2 *Variable Definitions, and Summary Statistics*

To assess the impact of R&D grants on innovation, we use innovation output. Separate analyses are conducted for the intensive and extensive margin responses. First, the intensive margin variable - the intensity of the innovation effort - is the number of patent applications (*Patent*) filed with the EPO, USPTO, and PCT via WIPO. Second, we measure the extensive margin variable - the decision to apply for a patent - (*Appl*) through a dummy variable that is equal to one for positive patent applications and is zero otherwise. Considering these international patent applications instead of patent applications at national offices has the advantage of avoiding enforceability bias and the specific criteria required to patent an invention across national jurisdictions. In addition, we consider applications instead of the number of patents granted because applications are closer to the time of invention, mitigate potential truncation problems in our sample due to the time of the examination process and improve our coverage rates in the post-intervention period (Bronzini and Piselli, 2016). Finally, we use patent families'

[17] Under the analysis period cover, multiple initiatives for SMEs were launched both under the Framework Programme 7 (FP7) and Horizon 2020. These support programs follow a bottom-up approach and encompass the following programs: Eureka-Eurostars, Fast Track to Innovation (FTI), and Future and Emerging Technologies (FET).

information to avoid double counting for the same invention.

Firm-level characteristics and additional outcome variables drawn from Amadeus are added to control for observable differences across the treated and control groups and to explore the heterogeneous effects of the SMEI program. The observable characteristics include country location, sector classification, firm age, size, intangible and tangible assets, and the patent stock.

For each firm, sector classification is defined at the one-digit industry classification code (NACE Rev.2) reported on the balance sheet information. Age is defined by using the date incorporation until the end of the sample. Size is proxied by the natural logarithm[18] of total assets owned by firm i at the end of the fiscal year. Total assets equal total book assets. Intangible assets are measured as the natural logarithm of the total of intangible products with useful life, with amortization that includes goodwill, software, research and development expenditure, and intangible rights. Tangible assets are measured as the natural logarithm of the total of physical assets that equals the book value of all tangible capital assets owned by the firm at the end of the fiscal year. Finally, the patent stock is defined as the cumulative number of patent applications filed at the EPO, USPTO, and PCT via WIPO. Debt outstanding is differentiated between short- and long-term debt, which equals the sum of nonequity liabilities. Short-term debt outstanding equals loans with a maturity of less than twelve months, whereas long-term debt outstanding has a maturity superior to twelve months.

Table 2.2 presents the summary statistics for the sample of the treated group and randomly selected control group according to the assignment of treatment status. On average, treated firms filed 0.223 patents, while the control group tended to file on average fewer patents (0.121). The pre-2014 and post-2014 policy intervention exhibit the same patterns, except that in the post-2014 policy intervention, treated firms filed 82.05 percent more patents than their counterparts. Concerning the firm characteristics, we observe that the firms that experience the treatment are younger, with an average age of 9 years, than the control group with an average age of 17 years. The mean size for the treated group is €1,019,680 and €842,391 for the control group. The mean of intangible assets is small for the treated group and for the control group with €785 and €128 of intangible capital stock, respectively. Both groups exhibit slightly similar tangible capital stock, with average tangible capital assets of €93,060 for the treated group and €96,182 for the

[18]For *Size*, *Intangible Assets* and *Tangible Assets* variables, we applied the inverse hyperbolic sine transformation $f(x)=log(x+(x^2+1)^{1/2}$, because of negative values report in company accounts.

control group. Finally, the treated group experienced higher innovation capacity with an average cumulative number of patent applications of 0.436 more than the control group.

Table 2.2 – Summary Statistics

	Treated Group			Control Group			
Variables	Mean	Max	Std.	Mean	Max	Std.	Diff
Outcomes variables:							
Patent	0.223	39	1.552	0.121	365	1.659	***
Patent pre-R&D grant	0.229	39	1.878	0.123	365	1.853	***
Patent post-R&D grant	0.213	15	0.858	0.117	281	1.314	***
Patent EPO	0.081	17	0.656	0.052	188	0.746	***
Patent WO	0.061	12	0.385	0.041	172	0.695	*
Patent US	0.079	17	0.774	0.027	54	0.357	***
Appl	0.079	1	0.270	0.061	1	0.240	***
Control variables:							
Age	9.758	73	10.714	17.480	1121	18.502	***
Size (log)	13.835	18.784	2.301	13.644	22.712	1.905	***
Intangible Assets (log)	6.666	17.217	6.215	4.854	19.722	5.199	***
Tangible Assets (log)	11.441	17.403	2.577	11.474	20.636	2.308	–
Patent Stock	0.436	56	2.328	0.130	776	2.284	***
Sample Size:		411			43,247		
Joint Orthogonality Test:				0.000			

Notes: This table presents the summary statistics of the main variables used in our matching procedure and estimations. Summary statistics are reported separately for the treated and control group. The treated group is composed of program winners in Phase 1 and 2, while the control group is composed of randomly drawn sample of European SMEs. The last column reports the difference for each variable (the t-test of equal mean) across two groups.
* $p<0.1$, *** $p<0.01$

Overall, the observed differences in the average observable characteristics suggest that the treatment is not randomly assigned and might reflect selection bias. We formally test the randomization of the treatment through an F-test of joint orthogonality that tests whether observable characteristics are unrelated to the R&D grant assignment. We reject the null hypothesis (i.e., *p-value* = 0.000) that the observable characteristics of the treated group are unrelated to these characteristics of the control group.

4.3 *Matching Samples and Samples Balance*

We emphasize that we reject that the observable characteristics are similar across groups. In R&D grant evaluations, this problem refers to selection bias in the treatment evaluation literature which can be expressed as follows::

$$E[Y_i^T|Recipient_i = 1] - E[Y_i^C|Recipient_i = 0] = \underbrace{E[Y_i^T - Y_i^C|Recipient_i = 1]}_{Causal\ Effect} + \underbrace{[E[Y_i^C|Recipient_i = 1] - E[Y_i^C|Recipient_i = 0]]}_{Selection\ Bias} \tag{2.1}$$

where Y^T and Y^C are potential outcomes conditional on treatment status, which cannot be directly observed in the control group ($Recipient_i$=1)[19].

To avoid this identification issues, the evaluation literature uses a large variety of econometric approaches, such as RDD, matching, DID, selection models, and instrumental variables. Following Blundell and Costa Dias (2000), to address the non-randomness of the samples (i.e., selection bias), to reduce heterogeneity in observable characteristics and to ensure the parallel trend assumption prior to policy intervention is that several counterfactual groups are constructed, conditioned on pre-intervention characteristics combine with a difference-in-differences (Mastrobuoni and Pinotti, 2015). The matching procedure consists by estimating the likelihood to receive the treatment for both recipient and non-recipients firms in our analysis sample, based on observable characteristics. The estimated propensity score is used to match a non-recipient control group with the same likelihood of being treated than recipient firms. Specifically, we use a one-to-one propensity score matching procedure without replacement on the year prior the R&D grant assignment separately for Phases 1 and 2 of the SMEI program conditioned on observable characteristics, which removes the selection biases of program winners. The matching procedure is augmented with a common support restriction to ensure an overlap between the groups[20].

We implement the propensity score by estimating a Logit model for the probability of R&D grants assignment $P(X_i)$ conditioned on the following observable characteristics X_i: country location (ten categories); industry classification; firm age; size; the stock of intangible and tangible assets; and the patent stock. Except for the country location, industry, and firm age, we use lagged observable characteristics to avoid endogeneity between the treatment assignment and the changes in firm characteristics (Boeing, 2016). We assess matching quality by using balancing tests, which compare the differences in

[19] To overcome the selection bias, propensity score matching procedure relies on the conditional independence assumption (CIA), which stipulates that for a set of observable characteristics exogenous to the treatment assignment, potential outcomes are independent (Rubin, 1974).

[20] Hence, a total of 26 (respectively 11) observations are dropped from the sample of treated firms due to common support in Phase 1 (respectively 2). Figure 2.2 present the estimated probability of treatment and propensity score distributions across both groups.

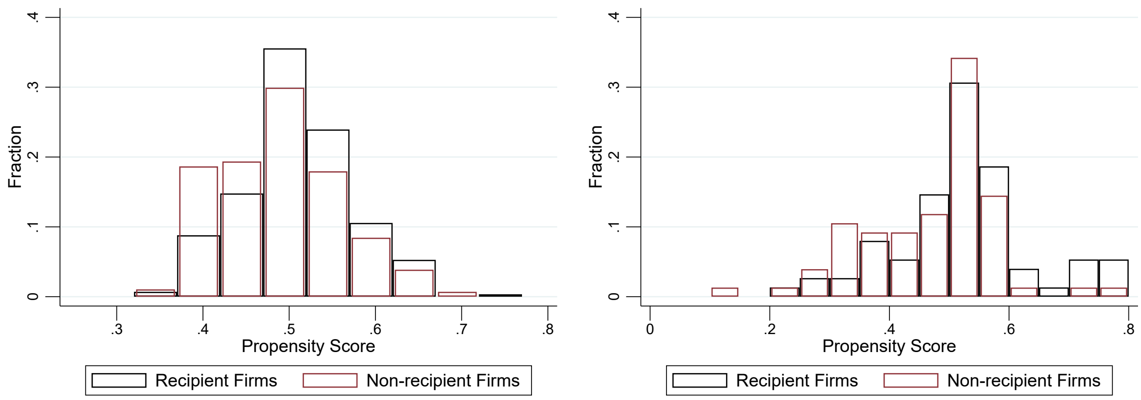
observable characteristics for the treated group relative to matching the counterfactual group. The balancing tests for Phases 1 and 2 are presented in Table 2.3. According to the matching procedure, the treatment and counterfactual group are similar in terms of the average observable characteristics, with limited and not statistically significant differences. In addition, we conduct robustness tests of our matching procedure. We re-estimate the probability of R&D grants assignment with a matched sample to ensure that any observable characteristics do not explain the probability of treatment assignment. Appendix Table 2.A.1 reports the estimated Logit specification before and after the matching. For Phases 1 and 2, any characteristics are statistically significant on the matched sample with a *Pseudo*-R^2 drastically reduced from 0.3 (respectively 0.25) to 0.01 (respectively 0.04) in Phase 1 (respectively 2). Therefore, firm characteristics are well balanced, and the treatment is randomized conditionally to this set of observable characteristics and control for the observable heterogeneity between the two groups.

Table 2.3 – Balancing Tests

	Phase 1			**Phase 2**		
	Recipient Firms	**Non-recipient Firms**		**Recipient Firms**	**Non-recipient Firms**	
Covariates	Mean	Mean	Diff	Mean	Mean	Diff
Age	11.980	12.415	0.434	13.039	13.934	0.874
	(0.627)	(0.582)	(0.082)	(1.298)	(1.109)	(1.708)
Size	13.972	13.933	-0.039	14.733	14.913	0.179
	(0.108)	(0.092)	(0.142)	(0.180)	(0.166)	(0.245)
Intangible Assets	8.196	8.371	0.174	9.131	9.201	0.069
	(0.345)	(0.312)	(0.465)	(0.667)	(0.655)	(0.935)
Tangible Assets	11.026	11.103	0.076	11.692	11.977	0.285
	(0.166)	(0.163)	(0.233)	(0.269)	(0.362)	(0.452)
Patent Stock	0.193	0.193	0	0.644	1.026	0.381
	(0.040)	(0.052)	(0.066)	(0.187)	(0.537)	(0.569)
Obs.	2,476	2,539		677	712	

Notes: This table compares the pretreatment mean of covariates for Phase 1 and 2's program winners with their counterfactual from one-to-one propensity score matching. For readability, country and industry dummies are not reported. Columns 3 and 6 reports the differences in the mean between the treated and control group. Robust standard errors are reported in parentheses.

The resulting unbalanced sample yield 5,015 and 1,389 firm-year observations in Phases 1 and 2, respectively.



(a) Phase 1

(b) Phase 2

Figure 2.2 – Propensity Score Distributions.

Note: This figure shows the estimated propensity score distributions across Phase 1 and 2 obtained using one-to-one propensity score matching within common support.

5 The Causal Effects of R&D Grants on Innovation Propensity

5.1 *Empirical Framework*

Our main objective is to estimate the causal effect of the SMEI program on innovation propensity. Based on the matching procedure described in Section 4.3 and according to the treatment status for recipient and non-recipient firms, our identification strategy implements a difference-in-differences (DID) specification. The matching procedure relies on the conditional independence assumption, which is satisfied if we control for all observable and confounding variables are know. However, it is implausible to observe all characteristics that condition firm's decision to apply. Therefore, combining matching and DID allows to control for selection bias based on observables and time-invariant unobservable firm characteristics. The causal effect is estimated as follows:

$$Y_{it} = \beta_0 + \beta_1 Recipient_i \times Post - Grant_{it} + \eta_i + \delta_t + \varepsilon_{it} \tag{2.2}$$

where Y_{it} is the outcome of interest for firm i in calendar year t. $Recipient_i$ is the key policy intervention variable that denotes the R&D grant assignment status, which is equal to one for recipient firms (i.e., treated) i and is zero otherwise. $Post\text{-}Grant_{it}$ denotes the post-intervention period (t_k>2014) that equals one for years 2015[21] onward and zero

[21] The policy intervention has occurred during the entire 2014 calendar year, with grant duration until two years (Phase 2), therefore we remove this period in the *Post-Grant* dummy.

otherwise. We include firm η_i and time δ_t fixed effects that control for firm unobserved heterogeneity in selective program participation and common country characteristics that would assign firm performance and participation. Because $Recipient_i$ is defined at the firm level, we cluster the standard errors within firms[22].

Firms do not file a patent application in each calendar year, depending on the stage of the project and R&D expenditures committed. In Phase 1 (resp. 2), at least 192 (resp. 56) firms in our sample of 568 (resp. 152) have one patent application between 2008 and 2017. The intensive margin response is a count variable, with a distribution usually skewed on the left coupled with a long right tail. Therefore, OLS estimates[23] are biased because the distribution of the count data does not fit the normal distribution of error terms in a log-linear specification. We use Poisson Quasi-Maximum Likelihood (PQML) estimator (Gourieroux et al., 1984; Guceri and Liu, 2019).

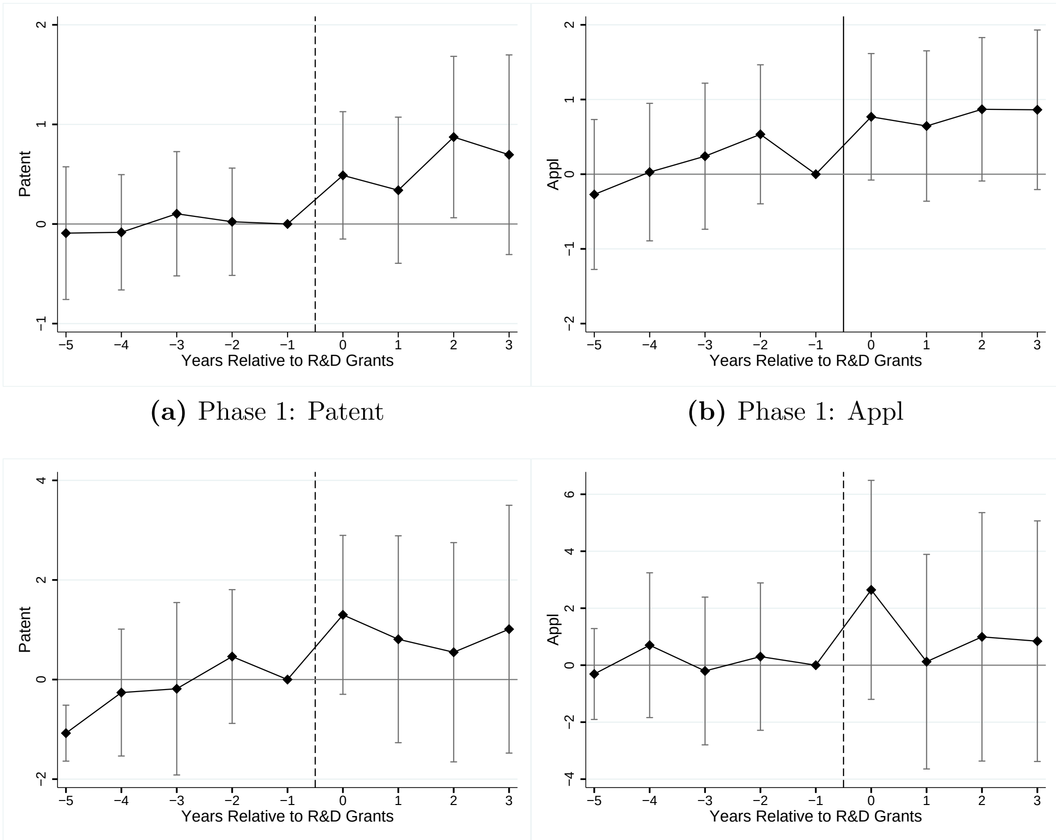
We focus on the interaction term $Recipient_i \times Post - Grant_{it}$[24] that allows us to estimate the average "*treatment effect on the treated*" (TOT). That is, this interaction term captures the change in outcomes (i.e., innovation propensity) between the pre- and post-intervention for recipient firms relative to non-recipient firms. In contrast to the recent findings from the fuzzy regression discontinuity design RDD (Bronzini and Iachini, 2014; Bronzini and Piselli, 2016; Howell, 2017) that uses a variation in the treatment around a threshold and estimates the local average treatment effect (LATE), our empirical framework exploits the entire treated population.

A natural experiment would have been to examine the exogenous assignment of R&D grants between program winners and the firms for which the business plan was rejected and then estimating the causal relationship between R&D grants and innovation propensity. Our data do not allow us to observe program-rejected applicants and implicitly, the score assigned to each project. Without randomization, our quasi-experimental framework relies on a matching procedure. However, the validity of our DID specification relies on the

[22]Consistent with the literature, we present results clustered at the firm level (e.g., Zwick and Mahon 2017, Yagan 2015, and Guceri and Liu 2019). However, following the argument of Bertrand et al. (2004), in the presence of serial correlation in the outcome, standard errors at the individual level could be biased even with clustering, resulting in overrejection of the null hypothesis of no causal effect. In robustness tests, our results are robust to permutation test (Ohrn, 2018; Chetty et al., 2009)

[23]For baseline estimates, we use the natural logarithm transformation ln(1+x) to account for zero in the outcomes.

[24]The interaction term refers to the interaction between two dummy variables for program winners (recipient firms), the estimated coefficient is uninformative on how R&D grants increase innovation propensity in real terms (euros). It is only informative on the crowding-in or crowding-out effect of the program.



(a) Phase 1: Patent

(b) Phase 1: Appl

(c) Phase 2: Patent

(d) Phase 2: Appl

Figure 2.3 – Event Time Difference-In-Differences Estimates: Pre-Trends Tests.

Note: Figure (a-d) presents the event study estimates β_t by Poisson QMLE and Logit from the specification (2.3) and corresponding 95 percent confidence intervals. The dependent variables are the number of patent applications (panels a-c) and a dummy variable for positive patent applications (panels b-d). The sample includes recipient and non-recipient firms in Phase 1 and 2 from the matched procedure around the policy intervention in 2014. The estimated coefficient is normalized to 0 in 2013. Each dot stands for the point estimate and can be interpreted as changes in innovation propensity compared to the year before the policy intervention (i.e., 2013) conditional on firm and calendar fixed effects. Standard errors are clustered at the firm level for Poisson estimator (panels a-c) and bootstrapped at the firm level with 200 replications for Logit estimator (panels b-d).

parallel trends assumption that in the absence of policy intervention, the non-recipient firms would have followed the same path than the recipient firms. To formally confirm the validity of the empirical framework, we implement an event study around the policy intervention, which allows us to use the null hypothesis of no pre-trends (Guceri and Liu, 2019). To address this concern, we implement the following specification:

$$Y_{it} = \beta_0 + \sum_{t=2008}^{2017} \beta_t [Recipient_i \times \mathbb{1}[Year_t]] + \eta_i + \delta_t + \varepsilon_{it} \tag{2.3}$$

where $Recipient_i$ is interacted with time year effects (we include a set of lags and leads around the policy intervention), and the interacted coefficient is normalized to 0 in 2013. Thus, the estimated effects β_t are relative to the year prior to the policy intervention.

Figure 2.3 reports the estimated coefficients on this set of leads and lags through specification (2.3) estimated by Logit and PQML[25]. They are interpreted as changes in the recipient firms' number of patent applications and the probability of patenting relative to the non-recipient firms compared to the period until five years before the implementation of the SMEI program. The point estimates on the intensive and extensive margin responses to the SMEI program show that there are no clear pre-trends for both Phases 1 and 2 before the R&D grants assignment. One exception is the point estimates for the number of patent applications for Phase 2 estimated from PQML specification. The point estimates show a declining trend before the R&D grant assignment, which suggests a pre-trend and casts doubt on the validity of our empirical framework for this specification[26]. We also perform a more formal test for the null hypothesis that the estimated coefficients for each lead in the pre-intervention period are equal to one another ($\beta_{-5} = ... = \beta_{-1}$). Coefficients for this regression in Figure 2.3 and the full set of regression results are report in Appendix Tables 2.A.2 and 2.A.3. In all cases, the F-test is not statistically significant with the *p-value* that exceeds the 10 percent level, which confirms our quasi-experimental framework and the causal effect identification. As mentioned, the only exception is that we do not reject the null hypothesis for the number of patent applications for Phase 2 estimated by PQML, with a *p-value* of 0.005.

5.2 *Effects of the SME Instrument Program*

Table 2.4 reports the main results from the specification (2.2). Panel A presents the results for the effect of public subsidies for Phase 1 program winners. Column (1) reports the estimated coefficients for the natural logarithm of the number of patent applications (i.e., the intensive margin) as an outcome variable by using OLS specification. The point estimate is positive, but it is only significant at the 10-percent level, which leads to an increase in the number of patent applications by 3.1 percent among recipient firms. Column (2) presents the OLS estimate for the extensive margin. The coefficient is positive and significant, which suggests that the causal effect of the SMEI program leads to a 3.7-percentage-point increase in the extensive margin. On average, this corresponds to a 45.5-percent increase in a firm's probability of patenting. Column (3) replicates

[25] Note that we report the corresponding figure for OLS regression in Appendix Figure 2.A.2. The visual evidence are similar to Logit and PQML specifications, suggesting no violation of the parallel trend assumption.

[26] In additional robustness tests, we replicate this specification with Negative Binomial estimator suggesting no changes in the recipient firms' number of patent applications, relative to non-recipient firms.

the results in column (1) using PQML specification. The point estimate is positive and statistically significant at the 10 percent level, which suggests that R&D grants increase the intensive margin response of the number of patent applications by 1.7 times relative to non-recipient firms[27]. The remaining column shows the extensive margin response on whether program winners have a higher probability of patenting, relative to non-recipient firms, by using a Logit estimator. The point estimate shows that R&D grants increase the probability of patenting by 1.6 times but only at the ten-percent level[28]. Our results emphasize that R&D grants of €50,000 increase firms' patenting activity at both the intensive and extensive margins. However, the baseline results are quite similar in terms of magnitude, which suggests that the primary effect of the R&D grants must be on the extensive margin response, and increases the number of firms that applied for at least one patent in the post-intervention period.

Panel B reports the results for the Phase 2 winners, which obtain average grants equal to €1,251,004. In all specifications, the point estimates are positive but statistically insignificant. These differences with the estimates in Panel A imply that the effect on Phase 2 winners does not imply an additionality effect on the patenting activities of recipient firms. A potential explanation for the absence of positive effects on firms' patenting activity, on both the intensive and extensive margins, might be that SMEs undertake radically new technology investments with a longer exploration and development time.

5.3 *Additional Results and Other Policies*

So far, we have focused on how the public subsidy impacts the patenting activities of recipient firms. In Appendix Table 2.B.1 and Table 2.B.2 we control for the natural logarithm of the amount of grant per winner. Columns (1-2) show qualitatively similar results but with higher magnitudes on the intensive and extensive margin responses relative to our baseline results. Interestingly, the R&D grant amount is only significant for the firm probability of patenting in Phase 2, but the main coefficient of interest is not significantly different from zero. However, the insignificant point estimates on the amount of the grant might be explained by the fact that we capture only the subsidy

[27] In Poisson regression model, estimates coefficient is interpreted as the factor change in the rate $e^{(\beta\gamma)}$. For a unit change in x, the expected count changes by a factor of $e^{(\beta)}$, holding all other variables constant.

[28] These results on the intensive and extensive margin response with respect to policy intervention as well as estimated magnitudes are in line with the literature on R&D subsidies public support. On northern Italian program, Bronzini and Piselli (2016) report that program winners increase on average by 1 the number of patents and 12 percent the probability of patenting on the post-intervention period. Concerning the SBIR program, Howell (2017) finds that Phase 1 winners increase cite-weighted patents (in log transformation) by 30 percent and by 9 percentage points the probability of patenting.

Table 2.4 – The Causal Effect of Phase 1 and 2 on Innovation Propensity

	OLS		Poisson	Logit
Dependent variable:	**(1)** *Log Patent*	**(2)** *Appl*	**(3)** *Patent*	**(4)** *Appl*
	Panel A. Phase 1			
Recipient*Post-Grant	0.031*	0.036**	0.529*	0.504*
	(0.018)	(0.017)	(0.291)	(0.293)
Obs.	5,015	5,015	1,697	1,677
Clusters (firms)	568	568	189	187
Pseudo-R^2	0.37	0.28	0.023	0.035
log-likelihood	–	–	-1,221.1	-684.0
	Panel B. Phase 2			
Recipient*Post-Grant	0.033	0.039	0.124	0.595
	(0.071)	(0.045)	(0.573)	(0.731)
Obs.	1,389	1,389	506	471
Clusters (firms)	152	152	55	52
Pseudo-R^2	0.61	0.51	0.027	0.085
log-likelihood	–	–	-774.6	-195.1
Firm FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes

Notes: This table presents estimates for the R&D grant effect on innovation propensity from specification (2.2). Recipient is a dummy variable equal to one for firms that receipt R&D grant (treated firms). Post-Grant is a dummy variable equal to one for years 2015 onward and zero otherwise. Recipient*Post-Grant denotes our main coefficient of interest, that corresponds to the differential change in innovation propensity across recipient and non-recipient firms. The dependent variables are the log transformation ln(1+ .) of the number of patent applications, the number of patent applications and a dummy variable for positive patent applications. Standard errors are clustered at the firm level for OLS and Poisson estimators and bootstrapped at the firm level with 200 replications for Logit estimator.
** $p<0.05$, * $p<0.1$

amounts in the year of intervention, and this effect might persist over a long time period.

During the post-intervention period, the program winners in Phase 1 can apply for the second phase of the SMEI program and receive an additional grant of a minimum of €500,000, which reinforces our main results for Phase 1 winners. Columns (3-4) of Appendix Table 2.B.1 replicate the specification as Table 2.4 by controlling for the subsequent Phase 2 applications within the post-intervention period[29]. The Phase 2 SMEI denotes a dummy variable that is equal to one if a firm receives a Phase 2 grant and is zero otherwise. In our main sample, a total of 46 program winners in Phase 1 received an R&D grant for the subsequent Phase 2. In 2015, the total amount of R&D grants was €1.7 million for ten recipient firms, €1.6 million for twenty-six recipient firms

[29]Our difference-in-differences specification is as follows: $Y_{it} = \alpha + \beta_1 Recipient_i \times Post_t + \phi Phase2SMEI_{it} + \eta_i + \delta_t + \varepsilon_{it}$.

in 2016, and €1.2 million for ten recipient firms in the last period. Point estimates are similar in terms of both statistics and magnitude for the intensive and extensive margin responses, while the Phase 2 SMEI estimates are positive but statistically insignificant at the ten-percent level. From these estimates, Phase 1 winner participants in the subsequent Phase 2 do not benefit from additional public funds, which confirms the R&D grant effect on the innovation propensity of recipient firms.

Under the leadership of the European Commission (EC) and the European Innovation Council (EIC), a wide range of public support has been implemented to stimulate innovation in SMEs. For example, we identified the following three important European subsidy programs: Eurostars (1-2); Fast Track to Innovation; and Future and Emerging Technologies. Among our sample of recipient firms, 36 received funds from these other European programs. In contrast to the SMEI program, these programs have in common the eligibility rule for public funds that require project consortia from different European members or associated countries. These policies could confound our main results and bias upward our main estimates. Appendix Tables 2.B.1 and 2.B.2 report the results for the intensive and extensive margins in Phases 1 and 2 by controlling for these R&D grant supports with a dummy variable that is equal to one for the recipient firms that receive public funds and is zero otherwise. For Phases 1 and 2, the results are robust after controlling for other innovation policies[30].

5.4 *Internal Validity and Robustness Tests*

Matching Procedure.— In our baseline results, we rely on a one-to-one matching procedure to construct counterfactual groups. We test whether our baseline specifications are robust to an alternative matching procedure, and we replicate specification (2.2) reported in Table 2.4 by using weight observations from the inverse propensity score of the R&D grant assignment. Inverse propensity score weighting (IPW) has an advantage compared to other matching procedures because it uses all observations in the control group[31] and creates a pseudo population in which the treatment is statistically independent of the outcome, conditional on observable characteristics X_i (Abadie, 2005). The weighting scheme

[30] These results on the impact of other European programs that support innovation in SMEs with respect to the policy intervention are in line with the existing literature. Czarnitzki and Lopes-Bento (2013) find no existing crowding-out effects on R&D intensity and employment for firms receiving R&D grants from the Flemish government and national or European programs. In the case of Eurostars (2008-2013) program, Hünermund and Czarnitzki (2019) find that the causal effect on employment and sales growth is not significantly different from zero.

[31] The control group refers to the population of European innovative SMEs randomly drawn from Amadeus and consists of 432,470 firm-year observations (see Section 4.1).

is implemented as follows:

$$W_i = [Recipient_i \frac{p}{P(X_i)} + (1 - Recipient_i)\frac{1-p}{1-P(X_i)}] \tag{2.4}$$

where $Recipient_i$ is a dummy for program winners that is equal to one and is zero otherwise, $P(X_i)$ is the propensity score conditional on observable characteristics X_i, and p is the unconditional probability of R&D grants assignment. Appendix Table 2.B.3 shows that the average observable characteristics according to the weighting scheme are well balanced across both groups. Table 2.5 reports the results with weighting observations. The results are robust to this alternative matching procedure. Only the point estimate in column (3) of Panel B is statistically significant compared to the baseline specification in Table 2.4[32].

Permutation Tests.— An important concern with our quasi-experimental framework is that standard errors can be biased by serial correlation and over reject the null hypothesis of no causal effect $\beta_1=0$ (Bertrand et al., 2004; Ohrn, 2018; Chetty et al., 2009). To address this concern and provide a placebo test, we implement a nonparametric permutation test that randomly draws 500 placebo samples. More specifically, with replacement, the treatment status is randomly assigned to firms to preserve the same number of treated and control firms as the baseline sample. We then replicate specification (2.2) of Table 2.4 for the intensive and extensive margin responses by using the placebo treatment as real and reiterate this procedure 499 times. The permutation test is performed from the PQML and Logit specifications[33]. Figure 2.4 Panels (a-d) shows the empirical cumulative distribution function (CDF) from the 500 point estimates of the placebo treatment on our outcomes. The vertical line represents the true treatment effect reported in our baseline results that re-estimate specification (2.2) from the Negative Binomial estimation, and we find a similar estimated coefficient to the table. The point estimate is not significantly different from zero.

Panel (a) reports the permutation test for the intensive margin variable in Phase 1 and the empirical CDF. The placebo effects are centered on zero with 30 point estimates that are larger than the real treatment effect that gives a nonparametric *p-value* of 0.06. In Panel (b), 15 point estimates are larger, which suggests a *p-value* of 0.03. These results suggest that the positive and significant effect of Phase 1's SMEI program on

[32] Recall from Section 5.2 that the visual evidence for the intensive margins in Phase 2 shows that there is difference in pre-trends using the PQML estimator, while Negative Binomial estimator does not. Therefore, we re-estimate specification (2.2) from Negative Binomial estimation and find similar estimated coefficient than in Table 2.4. The point estimate is not statistically different from zero.

[33] Note that we also perform through OLS estimates, suggesting similar results

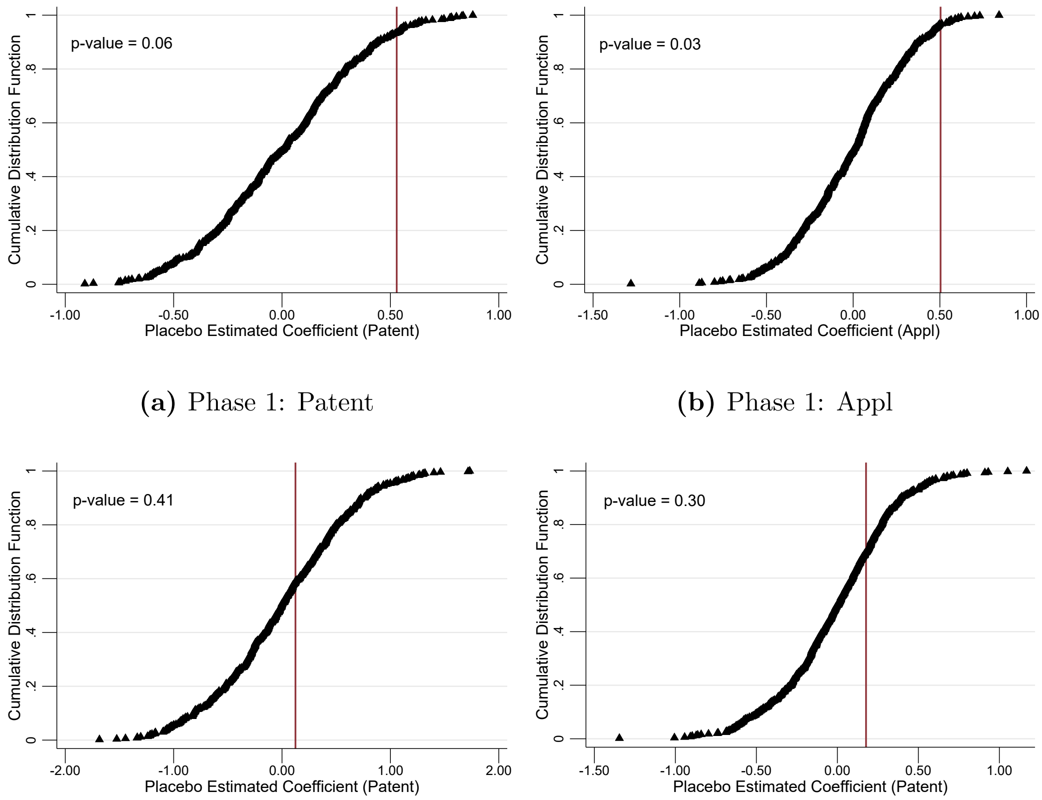
Table 2.5 – Inverse Propensity Reweighting

	OLS		Poisson	Logit
Dependent variable:	**(1)** *Log Patent*	**(2)** *Appl*	**(3)** *Patent*	**(4)** *Appl*
	Panel A. Phase 1			
Recipient*Post-Grant	0.033*	0.047**	0.343*	0.796***
	(0.017)	(0.018)	(0.176)	(0.299)
Obs.	405,121	405,121	112,123	111,593
Clusters (firms)	40,524	40,524	11,216	11,163
Pseudo-R^2	0.34	0.24	0.009	0.011
log-likelihood	–	–	-63,506.7	-38,090.7
	Panel B. Phase 2			
Recipient*Post-Grant	-0.032	-0.055	1.232*	-0.439
	(0.076)	(0.081)	(0.736)	(1.214)
Obs.	297,387	297,387	106,155	105,645
Clusters (firms)	37,290	37,290	10,619	10,568
Pseudo-R^2	0.52	0.28	0.009	0.011
log-likelihood	–	–	-73,817.5	-36,443.7
Firm FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes

Notes: This table presents estimates from specification (2.2) using an alternative matching procedure. Observations are weighted by the inverse propensity score. We estimate the probability to receipt R&D grant by a logit specification on the same set of covariates (see Section 4.2) and on the overall sample. Standard errors are clustered at the firm level for OLS and Poisson estimators and bootstrapped at the firm level with 200 replications for Logit estimator.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

innovation propensity is not driven by serial correlation and unobserved characteristics. In contrast, for Phase 2, the permutation test gives a nonparametric *p-value* of 0.41 and 0.30 for the intensive (Panel (c)) and extensive margin responses (Panel (d)), respectively. The nonparametric tests suggest that the effect of the R&D grant on the number of patent applications and the probability of patenting is statistically insignificant.

Additional Robustness Tests.— To further assess the robustness of our main results, Appendix Tables 2.B.4 and 2.B.5 provide additional robustness tests. A further concern of our quasi-experimental framework is that recipient firms may have strategically anticipated the policy intervention, which results in an "Ashenfelter Dip" effect (Ashenfelter, 1978). Consequently, recipient firms may have delayed their R&D investments to take advantage of the public subsidy or to increase the incentive to patent previous inventions by financing the patenting cost. These anticipations might result in an artificial increase in the post-intervention period. We address these strategic responses by consecutively removing the years of 2013, 2014 and 2013-2014. In Appendix Table 2.B.4, the point



(a) Phase 1: Patent

(b) Phase 1: Appl

(c) Phase 2: Patent

(d) Phase 2: Appl

Figure 2.4 – Permutation Tests.

Note: This figure shows the empirical cumulative density function (CDF) from placebo estimates for our main outcome variables. Figure (a-b) plot the empirical distribution for Phase 1, and Figure (c-d) for Phase 2. The four CDFs are constructed from 500 estimates of our main coefficient of interest by randomly chosen placebo recipient firms at each replication. The vertical line stands the estimated causal effect reported in baseline results (Table 2.4).

estimates for both Phases 1 and 2 increase slightly but remain quite similar to the baseline results. From this exercise, we mitigate the overestimation from the strategic anticipation of the R&D grant assignment. However, we are unable to disentangle the interaction between R&D investments and patenting[34], and recipient firms might conduct research in the pre-intervention period and file patent applications in the post-intervention period. An important assumption for our quasi-experimental framework is that our estimated causal effect is correlated with confounding factors that may affect the R&D grant assignment and our innovation propensity measures. We address this concern in Appendix Table 2.B.5 by including country-by-year, industry-by-year, and country-industry-by-year fixed effects, which control for country policies and industry

[34]According to the literature, patent applications are closely related to R&D investments and can occur simultaneously Hall et al. (1986).

shocks. Our results pass this exercise.

5.5 *Heterogeneous Responses to Firm Characteristics*

In this section, we further examine how the effect of R&D grants may differ from firm characteristics. The treatment effect could be heterogeneous and more pronounced for financially constrained firms (i.e., facing a higher cost of capital), which implies important policy implications for the program design. To explore the extent to which innovation propensity responds to observable characteristics, we interacted a heterogeneity indicator with our key policy variable. As ex-ante financial constraints, we consider firm age and firm size. These two heterogeneity indicators are usually used as criteria to distinguish between constraint and unconstraint firms (Zwick and Mahon, 2017; Criscuolo et al., 2019). Firm age and size are split along the median, based on the pre-intervention period (2008-2013), and we define a heterogeneity indicator to be equal to one if the age (size) of firm i is under the median and zero otherwise. The policy variable interacts with these heterogeneity indicators that allow estimating the heterogeneous causal effects.

Table 2.6 – Heterogeneous Responses to Firm Ex-ante Financial Constraints

	OLS		**Poisson**	**Logit**
Dependent variable:	**(1)** *Log Patent*	**(2)** *Appl*	**(3)** *Patent*	**(4)** *Appl*
Recipient*Post-Grant				
×Age	0.070**	0.063**	0.887***	0.874**
	(0.028)	(0.028)	(0.297)	(0.413)
×Size	-0.022	-0.034	-0.068	-0.467
	(0.025)	(0.026)	(0.299)	(0.388)

Notes: This table presents estimates for the R&D grant effect on innovation propensity. In the first row, firm age is defined as a dummy variable equal to one for the firms' age in the pre-intervention period below to the median of the firms' age distribution. In the second row, firm size is defined as a dummy variable equal to one for the firms' assets in the pre-intervention period below to the median of the firms' assets distribution. The dependent variables are the number of patent applications and a dummy variable for positive patent applications. Standard errors are clustered at the firm level for OLS and Poisson estimators and bootstrapped at the firm level with 200 replications for Logit estimator.
** $p<0.05$, *** $p<0.01$

Table 2.6 reports the heterogeneous responses to the R&D grants for Phase 1. Each cell reports the point estimate of the policy variable interacted with the heterogeneity indicator coefficient from a separate regression, where ex-ante financial constraints are defined by using the characteristics listed in the row heading. The first line of Table 2.6 shows that the effect of R&D grants is more pronounced among younger firms, (i.e., firms below 8 years). The heterogeneity responses suggest that there is a 7 percent increase in the intensive margin and a 6.3 percentage-point increase in the extensive margins. One possible explanation for young firms responding more to the R&D grant is that innovative firms are more affected by financial constraints. Therefore, the public support might alleviate the internal fund constraints and release credit market constraints (Bronzini and Piselli, 2016; Guceri and Liu, 2019). In contrast, the second line indicates that smaller firms are not more responsive on both the intensive and extensive margins. Interestingly, these findings contrast with recent empirical findings that find a stronger response to grants for smaller firms (Bronzini and Piselli, 2016; Criscuolo et al., 2019; Lach, 2002).

6 Mechanism of the Impact

What are the mechanisms that explain the R&D grant effect in Phase 1 on innovation propensity? R&D grants could improve innovation propensity through two main mechanisms. The first direct mechanism might improve the innovation propensity of SMEs through its positive impact on internal funds accumulation due to the subsidy amount. By contrast, R&D grants can directly reduce the user cost of capital toward financially constrained firms. We, therefore, explore more broadly the role of credit constraints in this section[35].

6.1 *Conceptual Framework: R&D Grant and Capital Market Imperfections*

The literature on financing innovation and investment decisions suggests that capital market imperfections impede innovation investments through a financing gap. Financial frictions are magnified under R&D projects and innovative investments due to the informational asymmetries that involve a biased evaluation of risky and uncertain projects by external investors. In addition, innovative firms lack adequate collateral to pledge. For these reasons, SMEs are more likely to be credit constrained (Hall et al., 2010).

To tackle this issue, we first consider a model of firm-level investment (Carpenter and Petersen, 2002) that provides a conceptual framework on how R&D grants affect SMEs' innovation propensity. Figure 2.5 (a) illustrates the case with perfect and imperfect capital imperfections. The capital investment level K is defined as the intersection of

[35] Note that we do not attempt to examine the exact mechanisms of the R&D grant effect, but shed more light on the market imperfection failures.

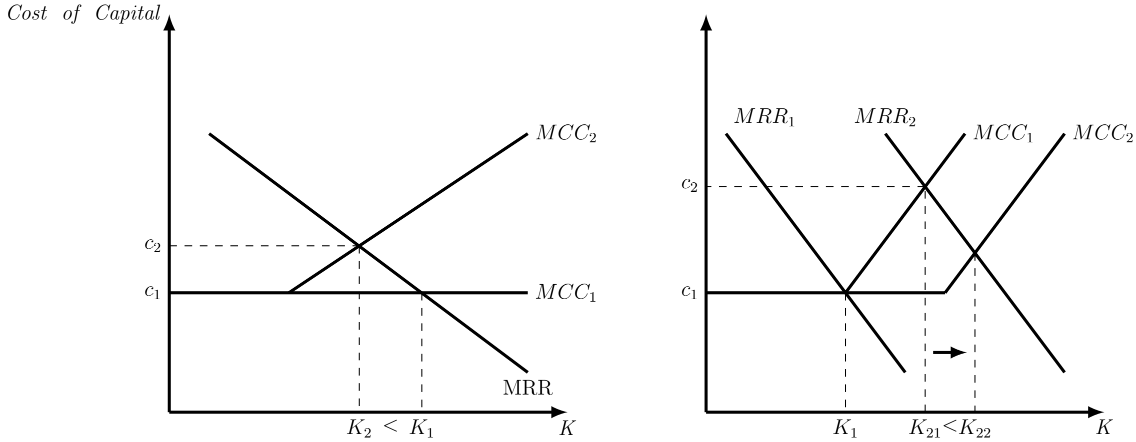


Figure 2.5 – Impact of R&D Grant on Cost of Capital.

Note: These figures show the theoretical impact of R&D grants on the cost of capital for firms facing perfect and imperfect capital markets.

the marginal rate of return (MRR) and marginal cost of capital (MCC) schedules. The downward-sloping MRR schedule ranks the projects and investment possibilities of a firm. The MCC schedule defines the opportunity cost of investment for different capital stock K. The MCC_1 illustrates the case of perfect capital markets, with the firm facing a horizontal cost of capital in that the firm relies on internal funds. By contrast, the MCC_2 schedule illustrates the imperfect capital markets case as upward-sloping in that the firm relies on costly external funds. In the case without public support and considering perfect capital markets, the capital stock (investment opportunities) is K_1, and the cost of capital is c_1. Conversely, in the presence of imperfect capital markets, the capital stock is K_2, and the capital cost of capital is c_2. Considering this toy model, the firms that face imperfect schedules (MCC_2) have a lower capital stock and higher capital costs than the firms that rely on internal funds.

We next turn to the case where we consider two firms with imperfect capital markets. Figure 2.5 (b) illustrates the case for financially unconstrained and constrained firms. First, an unconstrained firm has an MRR_1 that crosses the horizontal part of the MCC_1. By contrast, a constrained firm has an MRR_2 that crosses the upward-sloping part of the MCC_1 at the cost of capital c_2 and relies on external funds. The SMEI program has a direct effect on the cost of capital by displacing the MCC_2 to the right. For a similar R&D grant, the effect is stronger for financially constrained (upward-sloping part) than for unconstrained firms (horizontal part). R&D grants (cash shock) induce additional investment ($K_{21}<K_{22}$) and disproportionately reduce the cost of capital ($c_1<c_2$) for financially constrained firms. In addition, the program might have an indirect effect that

confers a certification effect on the recipient firms, similar to a job market signal (Lerner, 2000; Spence, 1973). This indirect effect discloses quality information on projects to external investors, which reduces the cost of capital via a reduction in the informational asymmetries between SMEs and investors.

Therefore, the conceptual framework provides a rationale for public support and the underlying mechanisms behind the causal effect. We can anticipate that R&D grants can have a causal effect on financially constrained SMEs by reducing the user cost of capital.

6.2 *The Causal Effect on External Capital*

To explore whether R&D grants affect the use of capital and ease SMEs' financing constraints, we re-estimate specification (2.2), where debt outstanding is our alternative outcome. Loan outstanding is differentiated between short (Log Loan) and long-term (Log Debt) maturity[36]. Table 2.7 reports the estimate from specification (2.2) of the effect of R&D grants on the use of outside capital for our Phase 1 sample. Columns (1) and (4) show that recipient firms increase their short-term debt use, while their ability to attract long-term debt is not improved. These results provide evidence that on average, public support alleviates the financing constraints for program winners on the use of liabilities with shorter maturity (i.e., less than one year).

Young and small firms might be more financially constrained than incumbents due to informational problems between managers (or entrepreneurs) and external investors and a lack of internal resources and collateral to pledge (Hall et al., 2010; Carpenter and Petersen, 2002). Therefore, R&D grants assignment could potentially increase the relevant information for external investors to a greater extent than for less opaque firms. To confirm this hypothesis, the remaining columns test whether young and small firms respond more than their counterparts[37]. As predicted, columns (2-3, 5-6) show a heterogeneous response from the R&D grant. The point estimates for short- and long-term debt are positive and statistically significant for young firms. This effect on debt outstanding appears to be larger for debt with a short maturity (i.e., 2.1 versus 1.6). Similarly, the point estimate in column (6) is statistically significant for small firms (i.e., 1.3). However, it is not different from zero for small firms in the use of short-term debt. We show that program winners in the post-intervention period attract further debt financing, which suggests that the SMEI program is more impactful among the firms

[36] Our measures of loan outstanding are transformed in the following form ln(1+x), given the existence of zero values reported in balance-sheet.

[37] To examine the effect of the grant on outside capital for young and small firms, we implement specification (2.2) with the ex-ante financial constraint measures used in Section 5.5.

that are more likely to be financially constrained.

Table 2.7 – Causal Effect on External Capital

Dependent variable:	*Log Loan*			*Log Debt*		
	(1)	(2)	(3)	(4)	(5)	(6)
Recipient*Post-Grant	0.692*	-0.006	0.386	0.557	0.073	0.086
	(0.410)	(0.489)	(0.503)	(0.421)	(0.451)	(0.446)
×Age		2.163***			1.626***	
		(0.647)			(0.628)	
×Size			0.654			1.315***
			(0.556)			(0.500)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,726	3,726	3,726	3,490	3,490	3,490
Clusters (firms)	474	474	474	481	481	481

Notes: This table presents estimates for the R&D grant effect on external capital from specification (2.2). The dependent variables are the logarithm of short-term (Log Loan) and long-term (Log Debt) debt. Standard errors are clustered at the firm level.
$^{*}p<0.1$, $^{***}p<0.01$

Overall, our findings on the positive effect of granted young and small firms on short- and long-term debt outstanding can arise through two mechanisms, namely, a resource or a signal effect. First, the resource effect could alleviate financing constraints through the grant amount awarded to a firm's internal funds accumulation, which allows it to test ideas and invest in R&D for prototyping and strengthening the balance sheet, reduces informal asymmetries and increases firms' solvency position (Lerner, 2000). By contrast, R&D grants might convene a signaling effect on investors concerning project quality, reduce informational asymmetries, indicate early-stage success, and lower the user cost of external capital[38].

To formally test this potential resource effect, we control for the size of the grant amount relative to total assets (e.g., Meuleman and De Maeseneire 2012). If the main mechanism is a resource effect that allows SMEs to develop ideas, a larger grant should have a substantial effect than smaller grants (Lerner, 2000; Howell, 2017)[39]. Appendix Table 2.B.6 reports the main results that control for the size of the grant. Point estimates confirm a positive and significant increase in the debt outstanding responses of young and small firms in the post-intervention period independently of the R&D grant size.

[38]Note that signal or certification effect requires competition among applicants and signal must be observable from investors as for selective subsidies instead of automatic public support (Colombo et al., 2011).

[39]In Phase 1, R&D grant amount awarded is the same for all program winners. Thus, the program design does not allow us to exploit variation in the fixed-effects specification.

Indeed, the point estimates associated with a lump sum of €50,000 relative to the total assets are statistically insignificant.

Taking these results together, our findings do not support that the resource effect is the primary mechanism through which R&D grants lessen financial constraints for Phase 1 winners. Instead of this mechanism, we find evidence that winning proof of concept grants might convey information on the project's quality to investors. Independent of the grant size, selection into the program is informative and yields a signal effect for young and small firms. Through the signal effect, the R&D grant alleviates informational asymmetries and reduces the user cost of capital. This result is consistent with some previous literature in the European context (e.g., Meuleman and De Maeseneire 2012). However, the signal effect contrasts with the evidence of Howell (2017) who finds that winning an SBIR grant alleviates financing constraints and enables firms to develop prototyping, which reduces uncertainty about the firm's quality.

7 Magnitudes of the SMEI Program and Policy Implications

An interesting perspective for evaluating the effectiveness of a direct subsidies program is to consider the overall magnitude in terms of additional patent and cost-per-patent applications attributable to the SMEI program. We apply the PQML coefficients in Panel A of Tables 2.4 and 2.5 to the number of recipient firms in Phase 1 to compute an estimate of the overall difference in the number of patent applications between the recipient and non-recipient firms. Multiplying the estimated coefficients (0.343 and 0.529) with the number of treated firms suggests that R&D grants have generated 97-150 additional patent applications for a total of 477 patent applications reported at the end of the period.

For Phase 1 winners, the total amount of the R&D grant awarded by the SMEI program was €14.2 billion in 2014 in the form of a lump sum of €50,000. By using this information with the number of patent applications generated in the recipient firms, we can calculate the direct cost-per-patent due to the program. Thus, the direct cost-per-patent generated in the program winners ranges from €94,000 to €146,392.

Note that we cannot perform a complete cost-benefit analysis of the R&D subsidies for at least two reasons. First, we are unable to account for the administrative cost involved in the policy intervention, such as application and management costs. Second, it is difficult to account for national public support, tax distortions across European countries, tax incentives[40] and knowledge spillovers into competitors and sectors that could positively (or negatively) impact patent applications. In addition, general equilibrium effects such as the increase in scientist wages are impossible to scale with our counterfactual framework. Nevertheless, our estimates permit us to give an overview of the effectiveness of the program. Our cost-per-patent is lower than previous findings in Italy[41] (Bronzini and Piselli, 2016). These differences can be partly explained by the policy design and regional context. The SMEI program is different from the Italian place-based program evaluated in Bronzini and Piselli (2016). First, the Italian policy provides a higher number of subsidies that cover project costs between €150,000 and €250,000, which is three and five times more than the Phase 1 grant in the SMEI program, respectively. Finally, the program is located in northern Italy. SMEs in the Emilia-Romagna region differ from the overall population of Italian and European SMEs and represent a small extent of firms inside the region, in the sense that they planned highly innovative investments.

A full welfare analysis should account for distortions, but these figures suggest that the R&D grants for proof of concept may be relatively costly as innovation incentives. However, three explanations may mitigate this negative assessment of the SMEI program. Patent applications are highly reliable to indicate innovation quality and the economic value of knowledge (Griliches, 1990; Kogan et al., 2017), but all inventions are not radical, and economic values are highly skewed. Another explanation is that recipient firms undertake additional R&D investments (which is beyond the scope of this chapter) with long development cycles until the patentability of their inventions, which reduces the figures within the post-intervention period. Moreover, we only rely on the estimated direct cost-per-patent, but the social value can be larger.

8 Conclusion

Industrial policies and R&D public supports are increasingly implemented across OECD and emerging countries to support private innovation research. Surprisingly, there is limited evidence on the causal effect of direct grants on innovation outcomes.

In this chapter, we examine an R&D subsidy program in Europe: the SMEI program. By using a unique dataset for the period of 2008-2017 of program winners and randomly drawn innovative European SMEs, we randomize the public support conditional on

[40] For example, several recent studies support the positive effect of tax incentives on investments (Agrawal et al., 2020), R&D spending (Guceri and Liu, 2019; Rao, 2016).

[41] Surprisingly, evidence on cost-per-patent or additional investments are scarce in the context of R&D subsidies.

observable characteristics. Then, we examine the effect of R&D grants on innovation outputs. Our findings from the quasi-experimental framework suggest that the SMEI program has a substantial effect on the firms' patent applications and the probability of patenting in the phase of proof of concept, whereas the effect is indistinguishable from zero in the phase of commercialization development. We also show that young and large firms are substantially more responsive to R&D grants. The evidence is partly consistent with the financial frictions that more severely affect startups and young SMEs[42]. An exploration of the underlying mechanisms suggests that R&D grants in the proof of concept phase have been used to raise a young firm's use of external capital, with a strong signal effect on external investors, which reduces the uncertainty about project quality. This is consistent with young firms that face financing constraints. Therefore, our results suggest that R&D grants are effective in stimulating innovative experimentation through realizing innovation output and securing the financial position of young firms. Finally, our findings in the proof of concept phase suggest that the direct cost-per-patent ranges between €94,000 and €156,000, which suggests a relatively expensive cost relative to the lump sum awarded.

From a policy perspective, we focus on the short-term effect. In particular, subsequent program cut-offs might attract applicants with different projects' quality and growth trajectories, which can change conclusions in the effectiveness of the program relative to our findings. Finally, we undocumented the relationship between R&D investments and productivity in response to policy intervention. Understanding these components is essential, and more work on the estimated effect is needed.

[42]An extensive literature provides evidence that public support through tax incentives and direct subsidies is greater for young and small firms: Howell (2017), Zwick and Mahon (2017), and Ohrn (2018) for the United States, Bronzini and Iachini (2014) and Bronzini and Piselli (2016) for Italy, and Guceri and Liu (2019) and Criscuolo et al. (2019) for the United Kingdom.

Appendix

2.A Additional Information on the Program and Identification Assumptions

In this section, we provide additional descriptive statistics and information on the matching process.

2.A.1 R&D Grant Geographical Distribution and Assignment Probability

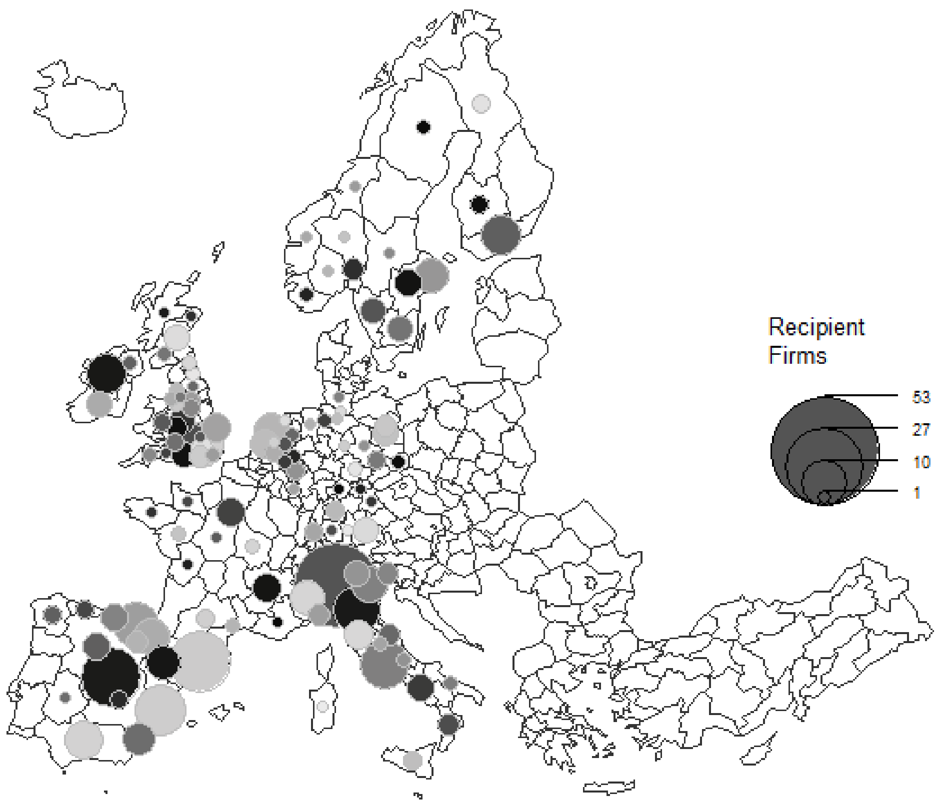


Figure 2.A.1 – Distribution of Recipient Firms in European SMEI Program, 2014.

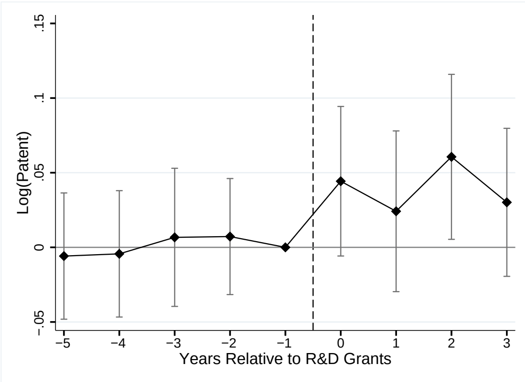
Note: This figure shows the distribution of recipient firms across selected European countries at the NUTS 2 level: DE, ES, FI, FR, IE, IT, NL, NO, SE, UK.
Source: Author's representation

Table 2.A.1 – R&D Grant Assigment Probability.

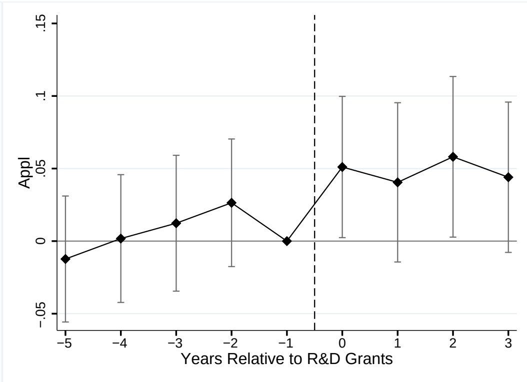
	Phase 1		Phase 2	
Dependent variable:	**(1)** *Before Matching*	**(2)** *After Matching*	**(3)** *Before Matching*	**(4)** *After Matching*
Age	-0.026***	-0.003	-0.035***	-0.007
	(0.008)	(0.010)	(0.015)	(0.022)
Size	0.149**	0.089	0.545***	0.005
	(0.069)	(0.085)	(0.124)	(0.173)
Intangible Assets	0.009	-0.005	0.057**	-0.012
	(0.016)	(0.021)	(0.028)	(0.037)
Tangible Assets	-0.052	-0.016	-0.068	-0.009
	(0.040)	(0.049)	(0.051)	(0.092)
Patent Stock	0.045	-0.016	0.132**	-0.055
	(0.052)	(0.109)	(0.052)	(0.047)
Country FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Obs.	37,570	568	34,634	152
Pseudo R^2	0.30	0.01	0.25	0.04

Notes: Columns (1) and (3) provide the estimates before the one-to-one propensity score matching, while columns (2) and (4) provide re-estimates after the one-to-one propensity score matching. Standard errors are clustered at the firm level.
** p<0.05, *** p<0.01

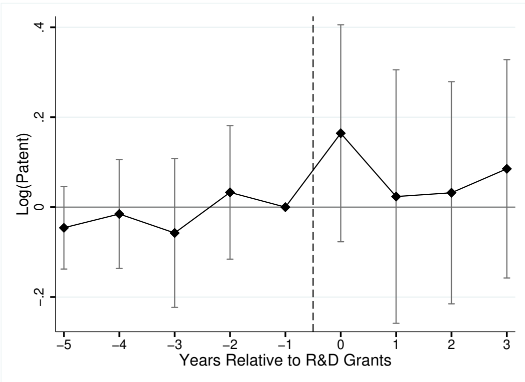
2.A.2 Difference-in-Differences Parallel Trends Assumption



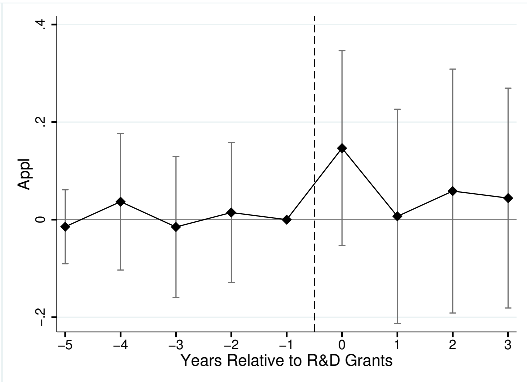
(a) Phase 1: Patent



(b) Phase 1: Appl



(c) Phase 2: Patent



(d) Phase 2: Appl

Figure 2.A.2 – Event Time Difference-In-Differences Estimates: Pre-Trends Tests.

Note: Figure (a-d) presents the event study estimates β_t by OLS from the specification (2.3) and corresponding 95 percent confidence intervals. The dependent variables are the number of patent applications (panels a-c) and a dummy variable for positive patent applications (panels b-d). The sample includes recipient and non-recipient firms in Phase 1 and 2 from the matched procedure around the policy intervention in 2014. The estimated coefficient is normalized to 0 in 2013. Each dot stands for the point estimate and can be interpreted as changes in innovation propensity compared to the year before the policy intervention (i.e., 2013) conditional on firm and calendar fixed effects. Standard errors are clustered at the firm level.

Table 2.A.2 – Pre-Trends Tests: Phase 1.

	OLS		Poisson	Logit
Dependent variable:	**(1)** *Patent*	**(2)** *Appl*	**(3)** *Patent*	**(4)** *Appl*
Recipient*𝟙[2009]	0.005	-0.003	0.377	-0.077
	(0.020)	(0.022)	(0.320)	(0.502)
Recipient*𝟙[2010]	0.006	0.010	0.386	0.198
	(0.022)	(0.023)	(0.397)	(0.521)
Recipient*𝟙[2011]	0.017	0.021	0.572	0.391
	(0.026)	(0.028)	(0.473)	(0.572)
Recipient*𝟙[2012]	0.018	0.035	0.492	0.657
	(0.025)	(0.028)	(0.471)	(0.591)
Recipient*𝟙[2013]	0	0	0	0
Recipient*𝟙[2014]	0.055*	0.059*	0.958*	0.860
	(0.030)	(0.030)	(0.528)	(0.597)
Recipient*𝟙[2015]	0.035	0.049	0.808	0.753
	(0.030)	(0.031)	(0.555)	(0.611)
Recipient*𝟙[2016]	0.071**	0.066**	1.342**	0.946
	(0.030)	(0.031)	(0.602)	(0.580)
Recipient*𝟙[2017]	0.041	0.052*	1.165*	0.954
	(0.026)	(0.028)	(0.696)	(0.611)
Firm FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
Obs.	5,015	5,015	1,697	1,677
F-test	0.16	0.43	1.56	2.02
p-value	0.976	0.830	0.816	0.732

Notes: This table presents the event study estimates β_t from the specification (2.3) and tests common trend assumption prior to the policy intervention between recipient and non-recipient firms. The interaction term Recipient*Year-j denotes our main coefficient of interest, which corresponds to an interaction between the binary indicator $Recipient_i$ for recipient firms and year effect set to 2009-2013. The estimated coefficient is normalized to 0 in 2013. Point estimates can be interpreted as changes in innovation propensity compared to the year before the policy intervention (i.e., 2013) conditional on firm and calendar fixed effects. *F-test* and *p-value* test the null hypothesis of no differences in the pre-trends prior to policy intervention. Standard errors are clustered at the firm level for OLS and Poisson estimators (columns 1-3) and bootstrapped at the firm level with 200 replications for Logit estimator (column 4).

Table 2.A.3 – Pre-Trends Tests: Phase 2.

	OLS		Poisson	Logit
Dependent variable:	**(1)** *Patent*	**(2)** *Appl*	**(3)** *Patent*	**(4)** *Appl*
Recipient*𝟙[2009]	-0.083	-0.029	-1.153***	-0.619
	(0.048)	(0.020)	(0.201)	(0.437)
Recipient*𝟙[2010]	-0.052	0.021	-0.337	0.387
	(0.065)	(0.061)	(0.758)	(1.157)
Recipient*𝟙[2011]	-0.094	-0.030	-0.261	-0.518
	(0.088)	(0.065)	(0.998)	(1.205)
Recipient*𝟙[2012]	-0.0004	0.013	0.385	-0.013
	(0.076)	(0.063)	(0.845)	(1.191)
Recipient*𝟙[2013]	0	0	0	0
Recipient*𝟙[2014]	0.126	0.131	1.222	2.319
	(0.128)	(0.129)	(1.007)	(2.089)
Recipient*𝟙[2015]	-0.013	-0.008	0.732	-0.196
	(0.156)	(0.120)	(1.254)	(2.204)
Recipient*𝟙[2016]	-0.005	0.043	0.471	0.675
	(0.129)	(0.119)	(1.260)	(2.203)
Recipient*𝟙[2017]	0.047	0.029	0.935	0.528
	(0.126)	(0.108)	(1.384)	(2.176)
Firm FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
Obs.	1,389	1,389	506	471
F-test	1.55	1.07	14.61***	4.60
p-value	0.189	0.371	0.005	0.330

Notes: This table presents the event study estimates β_t from the specification (2.3) and tests common trend assumption prior to the policy intervention between recipient and non-recipient firms. The interaction term Recipient*Year-j denotes our main coefficient of interest, which corresponds to an interaction between the binary indicator $Recipient_i$ for recipient firms and year effect set to 2009-2013. The estimated coefficient is normalized to 0 in 2013. Point estimates can be interpreted as changes in innovation propensity compared to the year before the policy intervention (i.e., 2013) conditional on firm and calendar fixed effects. *F-test* and *p-value* test the null hypothesis of no differences in the pre-trends prior to policy intervention. Standard errors are clustered at the firm level for OLS and Poisson estimators (columns 1-3) and bootstrapped at the firm level with 200 replications for Logit estimator (column 4).

2.B Additional Results and Robustness Tests

2.B.1 Additional Results: Robustness to Subsequent Phase 2 and other European Program.

Table 2.B.1 – Additional Results: Phase 1.

Dependent variable:	**(1)** *Patent*	**(2)** *Appl*	**(3)** *Patent*	**(4)** *Appl*	**(5)** *Patent*	**(6)** *Appl*
Recipient*Post-Grant	0.532*	0.584*	0.528*	0.472	0.524*	0.565*
	(0.282)	(0.315)	(0.295)	(0.295)	(0.289)	(0.330)
R&D Grant	0.002	0.042				
	(0.023)	(0.033)				
Phase 2 SMEI			0.017	0.571		
			(0.350)	(0.629)		
European-based program					0.417	0.340
					(0.440)	(0.665)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,697	1,677	1,697	1,677	1,697	1,677
Clusters (firm)	189	187	189	187	189	187
log-likelihood	-1,221.1	-683.1	-1,221.1	-683.5	-1,220.4	-900.7

Notes: Columns (1-2) has an identical specification to specification (2.2), but control the amount of the R&D grant received by recipient firms. Columns (3-4) is identical to columns (1-2) except that control for subsequent Phase 2 participation and columns (5-6) control for additional European programs that aimed to foster SMEs' innovation propensity. Standard errors are clustered at the firm level for the Poisson estimator and bootstrapped at the firm level with 200 replications for Logit estimator.
* $p<0.1$

Table 2.B.2 – Additional Results: Phase 2.

Dependent variable:	**(1)** *Patent*	**(2)** *Appl*	**(3)** *Patent*	**(4)** *Appl*
Recipient*Post-Grant	0.113	0.781	0.123	0.681
	(0.622)	(0.663)	(0.572)	(0.760)
R&D Grant	-0.006	0.102*		
	(0.031)	(0.056)		
European-based program			-0.215	-1.014
			(0.285)	(1.132)
Firm FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
Obs.	506	471	506	471
Clusters (firms)	55	52	55	52
log-likelihood	-774.5	-193.9	-774.4	-256.5

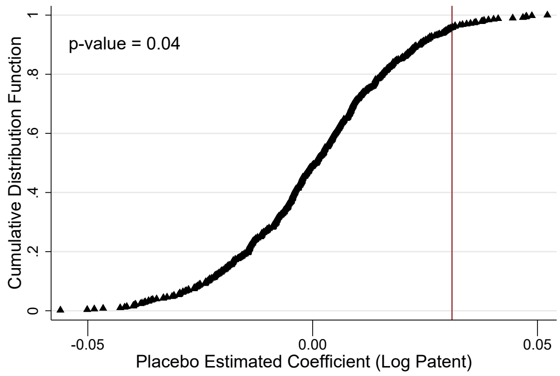
Notes: Columns (1-2) has an identical specification to specification (2.2), but control the amount of the R&D grant received by recipient firms. Columns (3-4) is identical to columns (1-2) except that control for additional European programs that aimed to foster SMEs' innovation propensity. Standard errors are clustered at the firm level for the Poisson estimator and bootstrapped at the firm level with 200 replications for Logit estimator.
* $p<0.1$

2.B.2 Additional Robustness Tests.

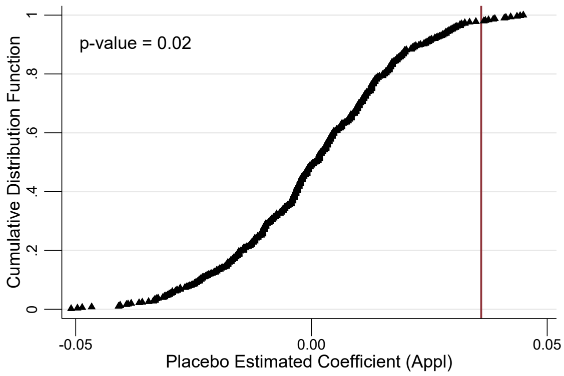
Table 2.B.3 – Balancing Test: Inverse Propensity Reweighting

	Phase 1			Phase 2		
	Recipient Firms	**Non-recipient Firms**		**Recipient Firms**	**Non-recipient Firms**	
Covariates	Mean	Mean	Diff	Mean	Mean	Diff
Age	17.702	19.438	-1.735	16.190	19.990	-3.800
	(12.257)	(18.523)	(1.394)	(14.220)	(19.053)	(3.854)
Size	14.116	13.909	0.206	13.369	13.953	-0.583
	(2.008)	(1.483)	(0.267)	(1.873)	(1.488)	(0.397)
Intangible Assets	6.657	5.576	1.080**	4.063	5.520	-1.457
	(5.418)	(5.196)	(0.481)	(5.125)	(5.211)	(1.030)
Tangible Assets	11.886	11.478	0.407	11.115	11.517	-0.401
	(2.601)	(2.309)	(0.332)	(2.815)	(2.325)	(0.550)
Patent	0.161	0.125	0.036	0.313	0.213	0.099
	(0.610)	(0.827)	(0.037)	(0.942)	(2.661)	(0.145)

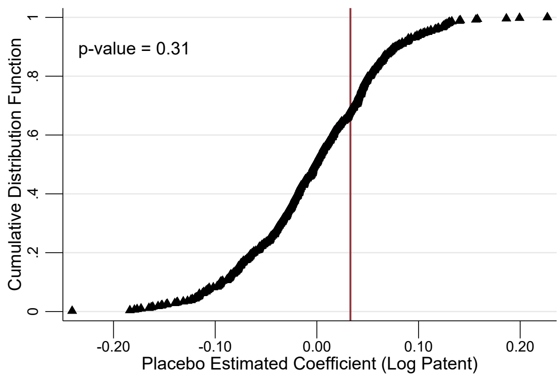
Notes: This table compares the pretreatment mean of covariates for Phase 1 and 2's program winners with their counterfactual from the inverse propensity score reweighting (Abadie, 2005). For readability, country and industry dummies are not reported. Columns 3 and 6 reports the differences in the mean between the treated and control group. Robust standard errors are reported in parentheses.
* $p<0.1$



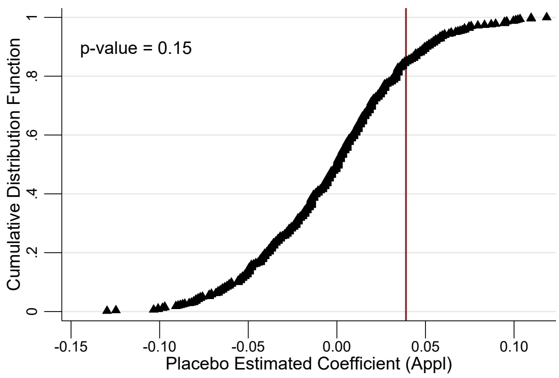
(a) Phase 1: Patent



(b) Phase 1: Appl



(c) Phase 2: Patent



(d) Phase 2: Appl

Figure 2.B.1 – Permutation Tests.

Notes: This figure shows the empirical cumulative density function (CDF) from placebo estimates by OLS for our main outcome variables. Figure (a-b) plot the empirical distribution for Phase 1, and Figure (c-d) for Phase 2. The four CDFs are constructed from 500 estimates of our main coefficient of interest by randomly chosen placebo recipient firms at each replication. The vertical line stands the estimated causal effect reported in baseline results (Table 4).

Table 2.B.4 – Anticipation Effects

Dependent Variable	Patent			Appl		
Drop:	**(1)** *2013*	**(2)** *2014*	**(3)** *2013-2014*	**(4)** *2013*	**(5)** *2014*	**(6)** *2013-2014*
			Panel A. Phase 1			
Recipient*Post-Grant	0.568**	0.631*	0.711**	0.494*	0.603**	0.630*
	(0.310)	(0.326)	(0.362)	(0.295)	(0.320)	(0.341)
Obs.	1,472	1,479	1,240	1,454	1,461	1,221
			Panel B. Phase 2			
Recipient*Post-Grant	-0.015	0.086	-0.093	0.604	0.703	0.747
	(0.590)	(0.626)	(0.622)	(0.683)	(0.676)	(0.861)
Obs.	436	437	371	405	406	344
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents estimates for the R&D grant effect on innovation propensity from specification (2.2) on a subsample that exclude pre-intervention years. Standard errors are clustered at the firm level for the Poisson estimator and bootstrapped at the firm level with 200 replications for Logit estimator.
* p<0.1, ** p<0.05, ***p<0.01

Table 2.B.5 – Additional Robustness Tests

Dependent variable:	**(1)** *Patent*	**(2)** *Appl*	**(3)** *Patent*	**(4)** *Appl*	**(5)** *Patent*	**(6)** *Appl*
			Panel A. Phase 1			
Recipient*Post-Grant	0.518**	0.521*	0.527*	0.472	0.508**	0.490*
	(0.249)	(0.293)	(0.290)	(0.316)	(0.246)	(0.287)
Obs.	1,697	1,677	1,697	1,677	1,697	1,677
			Panel B. Phase 2			
Recipient*Post-Grant	0.537	0.733	0.107	0.519	0.478	0.656
	(0.323)	(0.680)	(0.344)	(0.695)	(0.309)	(0.693)
Obs.	506	471	506	471	506	471
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Country × Time FEs	Yes	Yes	No	No	Yes	Yes
2-digit Industry × Time FEs	No	No	Yes	Yes	Yes	Yes

Notes: This table presents estimates for the R&D grant effect on innovation propensity controlling for additional policies. Columns (1-2) include country-by-year fixed effects to the baseline specification. Columns (3-4) include two-digit industry-by-year fixed effects. Columns(5-6) include country-two-digit industry-by-year fixed effects. Standard errors are clustered at the firm level for the Poisson estimator and bootstrapped at the firm level with 200 replications for Logit estimator.

* p<0.1, ** p<0.05

2.B.3 Mechanism of the Effect: Controlling for the Grant Amount.

Table 2.B.6 – Causal Effect on External Capital: Controlling for R&D Grant Size

Dependent variable:	*Log Loan*			*Log Debt*		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Recipient*Post-Grant	0.689*	-0.005	0.388	0.558	0.073	0.081
	(0.410)	(0.457)	(0.470)	(0.391)	(0.418)	(0.414)
×Age		2.154***			1.633***	
		(0.650)			(0.584)	
×Size			0.644			1.336***
			(0.556)			(0.466)
Grant Size	-0.370	-0.249	-0.177	0.109	0.185	0.330
	(0.250)	(0.239)	(0.208)	(0.241)	(0.228)	(0.207)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,726	3,726	3,726	3,490	3,490	3,490
Clusters (firms)	474	474	474	481	481	481

Notes: This table presents estimates for the R&D grant effect on external capital from specification (2.2). The dependent variables are the logarithm of short-term (Log Loan) and long-term (Log Debt) debt. Standard errors are clustered at the firm level. *$p<0.1$, ***$p<0.01$

Chapter 3

Information Frictions and Early-stage Investors: Evidence from a Crowd-Rating Platform

---

Summary of the Chapter

This chapter seeks to investigate the existence and importance of collective intelligence to reduce information frictions by informing potential early-stage investors about venture quality. My context is an online platform where the community score projects, offering new insights into how the crowd affects subsequent venture success. I motivate my analysis using a statistical extraction model, which predicts that higher-scoring from the crowd signaling information about project quality, reducing information frictions to potential early-stage investors. To overcome the challenge of unobservables correlated with scoring, I leverage the quasi-random assignment of evaluators to project with different leniency, which leads to random variation in the overall score. Using this exogenous variation, I find no evidence that scoring from the crowd predicts subsequent venture success in the short and medium-run. In comparison, naïve OLS estimates show positive correlations between the aggregate score and subsequent venture survival and employment, suggesting selection bias. Overall, my findings suggest that the crowd is unlikely to be an effective choice for revealing information about venture quality and reducing information frictions.

Classification

JEL Classification: D81, G24, G4, O3.

Keywords: Information Frictions, Entrepreneurship, Early-stage Investors, Crowd-Rating.

Acknowledgments for this chapter

I am grateful to Nadine Levratto for her advice and continued support. Finally, I thank Patrick Cantelli and Arnaud Adrion of Wirate and all the others who provided the data and presented the platform.

Contents of the Chapter

1 Introduction

Venture capitalists (VC) and angel investors provide a substantial source of external funding and resources (i.e., monitoring, value-added services, and control rights) to early-stage ventures with high growth potential (Kaplan and Lerner, 2010; Gompers and Lerner, 2001). However, uncertainty associated with the quality of early-stage ideas and the difficulty to access performance records raised severe challenges on the screening process. Early-stage investors face information frictions that became more relevant over the last decade. For example, Ewens et al. (2018) document that technological shocks have remarkably decreased the cost of starting a new venture, increasing uncertainty about the project quality for early-stage investors in the U.S. Yet remarkably little is known on investors' ability to screen early-stage ventures and how ex-ante assessments have predictive power for subsequent outcomes.

In this chapter, I examine whether early-stage investors could learn from the crowd about venture quality and how this information affects investor decision-making strategies. To address these questions, I use an analysis sample of 500 ideas and ventures that launched a project on an online platform. In the platform, early-stage venture founders present a pitch and the main information related to their ideas accessible to all potential evaluators registered. I combine these statistics spanning from 2015-2019 with data on fundraising, survival, employment, and web traffic outcomes. I then match ventures and founders to observable characteristics.

This unique analysis sample allows us to shed light on investors' ability to screen ideas and update beliefs based on evaluation from the crowd to resolve information frictions. Most previous research has focused on incubators and accelerators programs (e.g., Gonzalez-Uribe and Leatherbee 2018 and Hallen et al. 2014) or business plan competitions (e.g., McKenzie 2017, Fafchamps and Woodruff 2016). While these papers offer evidence on how these programs support innovative startups and help them to attract external funding, they typically rely on a panel of experts that score each venture. Few studies examine an emergent source of financing, crowdfunding (e.g., Hildebrand et al. 2017, Mollick and Nanda 2016, and Mollick 2013). However, papers that examine the role of the crowd to produce valuable signals on venture quality as could expert opinions are scarce. To my knowledge, this chapter is the first to provide evidence on the role of the crowd to screen early-stage venture projects.

The analysis is divided into three-part. First, to provide explanations and insights for my analysis, I developed a simple model of signal extraction based on the statistical discrimination literature (Aigner and Cain, 1977; Phelps, 1972). The model proposes that potential early-stage investors observe a noisy signal from the aggregate score of the crowd about the project's quality, and update beliefs according to this signal and their own information. I assume that the signal is informative and can reduce information frictions between ventures and investors and those early-stage investors maximize the expected payoff for their investment decision. Thus, projects scoring higher are evaluated as higher quality and are more likely to receive external funding from early-stage investors. However, decision-making strategies could be associated with the precision of the signal and also to a cut-off rule in the sense that investors may set higher or lower thresholds for specific categories.

This conceptual framework yields two propositions that are tested in my identification strategy. Using selection on observables I estimate the impacts of the signal contained on the evaluation from the crowd and allow potential early-stage investors to have different thresholds for projects. However, it is challenging to examine the impacts of evaluators' ex-ante assessment because crowd-rating is endogenous and will be correlated with the error term. First, the decision to evaluate certain projects is not randomly assigned, relying on the principle of self-selection. For example, the attractiveness and how evaluations are determined could depend on several external factors unrelated to project quality, such as the actual number of active evaluators on the platform, but also on the launch timing. Second, it is challenging to distinguish between the causal effects of a project evaluation from venture characteristics that could affect subsequent financing events. For example, the founding team characteristics (i.e., serial entrepreneur, degrees) could positively influence assessments, then influencing the investment decision (Bernstein et al., 2017).

This chapter addresses the identification challenges in the context of a crowd-rating online platform, by exploiting plausibly exogenous variation in the scoring process from the quasi-random assignment of ventures (or projects) to evaluators who differ in their leniency. In my baseline specification, I measure evaluator leniency as the average score in other ventures an evaluator has scored during an application round. The evaluator leniency measure is highly predictive of the crowd-rating, but uncorrelated with observable ventures characteristics. This instrumental variable approach is similar to Chen (2018) and Farronato et al. (2020), which use reviewers' assignment to estimate the causal effects of information disclosure from online platforms on consumers' choice[1].

[1]This instrumental variable identification strategy is related but a modified version to that used in

My analysis starts by documenting that evaluation from the crowd has a negative but statistically insignificant causal impact on the likelihood to have made a deal with angels and VC as of one and two years after the application process. Even controlling for venture observable characteristics, I estimate that one standard deviation in the aggregated score for a project leads to a 1.5 percentage point decrease in the probability of subsequent financing as of one year after the evaluation process, a 19.7 percent change, but remains statistically insignificant at conventional levels. However, this impact indistinguishable to zero is not caused by a homogeneous overall score from the crowd, and the venture outcomes being similar for all ventures. For example, a project at the 90th percentile has 1.5 more times subsequent financing events over the next year than a project at the 10th percentile of the crowd-rating distribution. These results suggest that early-stage investors are not sensitive to the score in the evaluation process.
I also find that the predictive power of the crowd varies across the seven questions answered by each evaluator. Indeed, each evaluator scored the projects on an assessment of success, usefulness, originality, ambitiousness, feasibility, affection, and societal and environmental aspect. For example, a one standard deviation increase in the score on the success assessment for a project increases the probability of subsequent funding rounds as of one year after the evaluation process by 1.8 percentage points, relative to an average probability of 7.5 percent. I also find that a higher average feasibility score is positively associated with the likelihood of subsequent financing by angels and VC in the short-run (0.015, s.e.=0.008). In contrast, the remaining criteria have no predictive power for early-stage investors. However, I caution firm interpretation of these results given concerns about selection on unobservable in this OLS estimates.

How would the informative signal from the crowd impact venture outcomes? A potential explanation of my findings is that a higher score reflects a higher project quality conditional on venture characteristics, which are correlated with the screening process of early-stage investors (i.e., selection) and subsequent financing events. Alternatively, certain projects may be more able to attract attention to the community, influencing the confidence of founders. Consistent with selection bias, my OLS estimates show positive correlations between the score and subsequent venture outcomes, even when I add control variables. To address this concern coming from the nonrandom evaluation and selection process, I estimate how the impact of the score is due to the causal effect following Altonji et al. (2005)[2]. I use selection on observables quality determinants to

contexts other than an online platform. See for example Bhuller et al. (2020), Di Tella and Schargrodsky (2013), Dobbie et al. (2018), and Aizer and Doyle Jr (2015) to investigate the impact of crime sentences.

[2]In particular, I follow several tests derived from the insights of Altonji et al. (2005), but that leverage

access the potential bias of omitted variables that explains the estimated impact. I show that the crowd-rating impact falls when I control for observable venture characteristics, suggesting potential selection bias in OLS.

In the second part of the paper, I examine the causal impacts of crowd-rating on venture real outcomes as a measure of early-stage success. I continue to find that using the crowd to evaluate projects does not result in a change in the probability of venture success as of one year after that ventures launched a project on the online platform. conditional on observable characteristics. I further find no evidence of positive impacts of crowd-rating in the medium-run despite the heterogeneity in the score. These results contrast with the positive associations in the short-run from OLS estimates. However, my estimates are often sufficiently precise to reject effects of the evaluation process.

In the third part of the paper, I examine how the impacts of crowd-rating are driven by venture and team characteristics. I also do not find statistically significant heterogeneous effects for subsequent financing events, venture survival, and employment. Overall, the effects of the crowd-rating based on venture and team characteristics are larger than baseline estimates, but precisely estimated to allow me to reject causal effects among these subpopulations. There are some exceptions to the overall pattern of impacts indistinguishable from zero. I find suggestive evidence that crowd-rating causes a reduction in the probability of venture survival in the short and medium-run among the group of projects at very early-stage, such as business ideas. The predictive power of the crowd for this group is large and significant. Conditional on observable venture characteristics, one standard deviation decreases in the score experienced by a venture thus decreases the probability of survival over the next year by 25.9 percentage points, a 31.8 percent decrease, and by 32.7 percentage points over the next two years. A different pattern emerges for ventures at a later stage development. Among this group, which comprise roughly half of the analysis sample, the score from the crowd positively impacts the probability of venture survival within one year, a 14.4 percent increase from the mean. Since the observable characteristics across these groups are highly similar, reflecting the prior mean for project quality, these heterogeneity results on the development stage suggest that founders are sensitive to information provide by the crowd about the quality of their project conditional on the development stage, consistent with the Bayesian updating framework (Howell, 2019). Finally, ventures that have at least one serial entrepreneur in the founder team are more responsive to the crowd-rating and increase

different statistical assumptions to assess the coefficient stability relative to the explanatory power of observable and unobservable variables. For further details on the coefficient stability approaches, see Bellows and Miguel (2009), Gonzalez and Miguel (2015), and Oster (2019).

their team by at least one employee (i.e., an 82.3 percent increase from the mean), relative to ventures for which it's the first entrepreneurial experience over the next two years.

Taken together, these results shed light on the inherent difficulty of screening and identifying ex-ante which ventures have high growth potential, even among a sample of projects a different development stage (idea, market fit, launched innovation). This is consistent with the concern that angels investors and venture capitalists face on the investment selection process and the risk in entrepreneurial finance (Kerr et al., 2014; McKenzie and Sansone, 2019; Kaplan et al., 2009).

This chapter contributes to several strands of the literature. The chapter relates to the information frictions in early-stage venture finance and how alternative assessment of project quality could reduce information asymmetries and search frictions (Howell, 2019; Ewens et al., 2018; Tian and Wang, 2014). To my knowledge, I am not aware of observational or experimental (quasi-experimental) studies on how relying on the crowd impacts ventures and signal project quality to the market, in particular using data from France. The most closely related paper is Cao (2020), which finds that a crowd-based online platform increases the probability of subsequent financing events as of the product launch, providing a signal of traction. A potential explanation for the contrasting results with this chapter is the functioning of the platform that used cumulative upvotes (i.e. clickthroughs for liking products) providing ranking among products. Relative to this paper, the granularity of information is smaller with fewer projects and users' community. Since I investigate the impact of the crowd-rating on subsequent financing events and venture success, my results are not consistent with Cao (2020) that information aggregation produces a signal that aims to reduce information frictions for early-stage investors and predict entrepreneurial success.

The chapter also contributes to the economic literature on predicting which early-stage ventures will succeed with high growth potential. My results are consistent with prior evidence that ventures on the earliest stage are difficult to evaluate and predict survival, employment, and traction (McKenzie and Sansone, 2019; Kerr et al., 2014), while some studies find that relying on expert judges to score projects and the probability of subsequent success (Fafchamps and Woodruff, 2016; Howell, 2019; Åstebro and Elhedhli, 2006). However, these studies examine the predictive power of business experts in the context of specific venture competition, which can be time-consuming and costly to implement (Howell, 2019; McKenzie, 2017), and provide correlation evidence (Scott et al., 2020; Åstebro and Elhedhli, 2006). This chapter is able to address these limitations, leveraging the crowd to resolve information asymmetries about project quality and using quasi-random assignment of evaluators to address concerns about correlated unobservable characteristics.

The chapter also contributes on the economics of online review databases. Online platforms that aggregated reviews revealing information and signals to update beliefs (Anderson and Magruder, 2012). A large series of studies examine the impact of online platforms as eBay (Cabral and Hortacsu, 2010; Lucking-Reiley et al., 2007), Amazon (Chevalier and Mayzlin, 2006), Yelp (Luca, 2016; Anderson and Magruder, 2012) on the responsiveness of customers to signals[3]. However, papers that document how early-stage investors and entrepreneurs learn in the sense of information revelation about project quality are scarce. This chapter sheds light evidence that the crowd-rating fails to highlight project quality and subsequent success, but are relevant for improving evaluation in a crowd setting.

The remainder of the paper is structured as follows. Section 2 provides background on the crowd-rating online platform and presents the data. Section 3 presents a model of signal extraction. In Section 4, I discuss the identification strategy, instrumentation, and its validity. Section 5 presents the main results for the evaluation from the crowd and Section 6 concludes.

2 The Crowd-Rating Platform and Data

This section introduces crowd-rating online platform, a website used by entrepreneurs and startups to evaluate new business ideas from the community. Then, in Section 2.2, I describe sample selection and present summary statistics in Section 2.3. Finally, Section 2.4 relates sample representativeness to the french startups' ecosystem.

2.1 *The Crowd-rating Platform*

Identify accurately ex-ante characteristics that startups, in particular, first-time founders will succeed is a primary interest to early-stage investors. However, a recent reduction in experimentation that reduces the entry barrier has increased quality uncertainty about startups' profitability (Ewens et al., 2018; Howell, 2019). In the past decade, business plan (i.e., or pitch) competitions have gained popularity in both developed and developing countries to attempt to select promising startups. This approach typically

[3]See also recent studies on Alibaba and Taobao online platforms on the effects of online reputation on importers Chen and Wu (ming) and consumers with asymmetric information Li et al. (2016).

relies on founders present their ideas to a panel of judges that score proposals (McKenzie and Sansone, 2019; Fafchamps and Woodruff, 2016)[4]. However, evidence suggesting effectiveness on identifying which ventures subsequently performances are inconclusive.

An alternative approach to evaluate venture ideas is to rely on collective intelligence. Wirate was founded in January 2015 with the main objective to rate early-stage ventures, connecting founders and potential investors. It is an online platform that attracts an online community of users - *potential investors, experts, coaches, and tech lovers* - that grew rapidly. Since January 2015, the platform recorded over 7,000 active users, which rate projects and provide feedback. Users register on the platform through their name, record their status as well as their main sector specialization[5]. The econometrician does not observe information record on the platform.

The platform allows the founders or team member to register a project. For that purpose, founders create a venture profile describing the project name, phase of development, a pitch, a video, a business plan, additional information on team members connected to their LinkedIn, and the location of the venture. Figure 3.1 shows an example of a project application on the platform, describing the homepage for each project. Between January 2015 and December 2019, 1254 projects were launched on the platform with a large increase in project application since 2016[6].

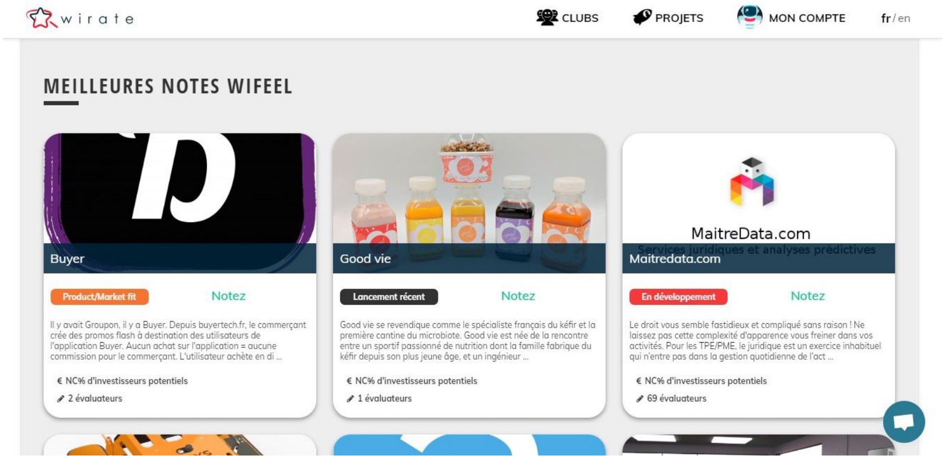
A key feature of the platform is that at each project application, the project page is featured on the platform homepage. All projects are listed on the online platform. Therefore, all the content of the projects page is accessible to the user community (i.e., evaluator on the rest of the paper) and can rate startup ideas based on a shortlist of questions. For each project, evaluators score the idea on eight questions that correspond to *success*, *usefulness*, *originality*, *ambitiousness*, *feasibility*, *affection*, and *societal and environmental impact*[7]. These different criteria scores are averaged into a final score. Average score is aggregated among all evaluators to create a final crowd-rating score. Evaluators score individually and observe only their own average score as well as the average overall crowd-rating. Note that evaluators observe in real-time the number of

[4]Similarly, there are investment readiness programs that evaluate high growth potential projects with the objective to increase the pipeline of quality investment opportunities for external investors. For a review, see Cusolito et al. (2020)

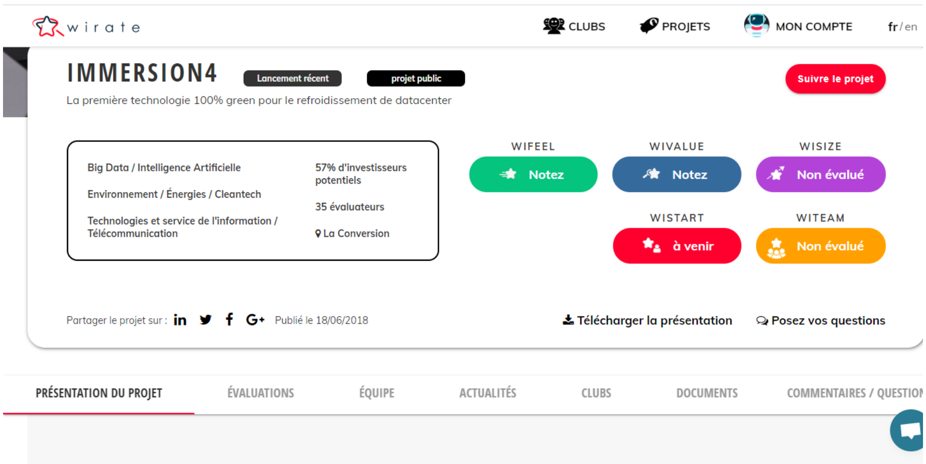
[5]Users of the online platform can select among 9 status items, such as evaluator, business angel, mentor, coach, tutor, expert, guide, private investor, and founder.

[6]The platform was launched in January 2015. For this year, 35 projects registered while 151 were recorded in 2016, an increase of 116%.

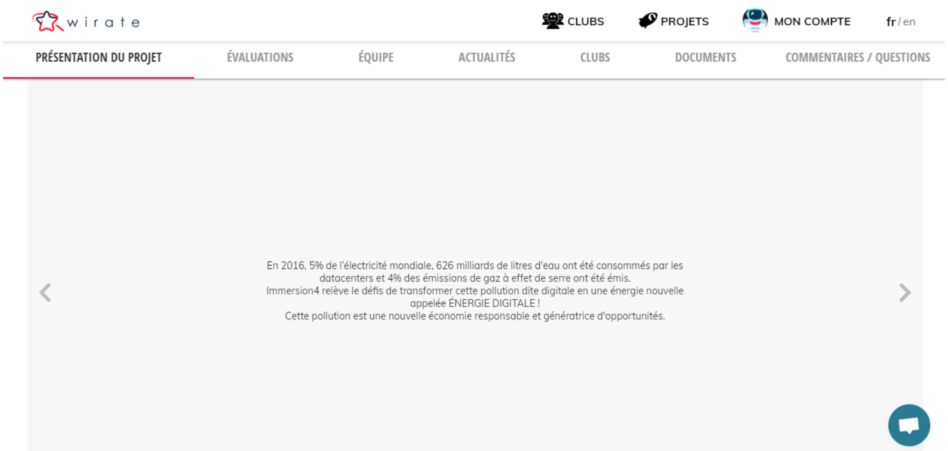
[7]See Appendix B for further details on the scoring process and questions



(a)



(b)



(c)

Figure 3.1 – Screenshots from a Example of Platform Web Interface.

Notes: This figure presents three screenshots of the web interface. Panel A shows the platform home page which lists all projects. Panel B shows an example of a project home page which contains a project's information available to upvoters, while Panel C shows an example of pitch.

upvoters but the score information only if they evaluate a specific project. In contrast, the econometrician observes all average scores related to the eight criteria but not the individual evaluator's score.

In the context of an online platform design with crowd evaluation and information crowdsourcing of early-stage ideas, the digitized access can enable large visibility and participation of a community to create and evaluate, lowering both cost and geographical barriers. Wirate provides three key contributions. First, the crowd-rating process allows anyone that has access to the online platform to self-select in participation. This allows to reach a large audience that provides screening of early-stage ideas from a hundred users relying on the collective intelligence system. The aggregated evaluation could complement or substitute expert judges to signal the quality of new ideas (Mollick and Nanda, 2016). Second, projects increase their visibility on the french startup ecosystem from various actors such as potential customers and potential investors. Projects' idea visibility is directly impacted through the actual number of upvoters, higher upvoters suggesting higher attractiveness. Projects with larger number upvoters are more likely to be evaluated on the platform, increasing precision. Thus, the crowd-rating could directly impact potential investors' decisions. A favorable average rate can send a positive signal on the high-firm growth potential reducing information asymmetries between startup and external investors. In addition, the crowd-rating can be an argument to attract investors during pitches or business plan. Finally, the average rate from the crowd could impact the founders' own perception of the idea and can be used as a tool for reducing demand uncertainty[8]. For example, a negative signal from the crowd can alter the perception of the idea's potential and how the project requires modification to attract potential customers. This signal is exacerbated for first-time entrepreneurs without experience.

2.2 *Sample Selection*

Crowd evaluation. My primary sample consists of all early-stage ventures or entrepreneurs. I use information on ventures from a database hosted by Wirate, which contains all ventures register on the online platform spanning from February 2015 to December 2019 who attend a crowd evaluation of their ideas. There are 1254 projects in this sample.

Starting from the raw dataset, I impose first restrictions to obtain my primary

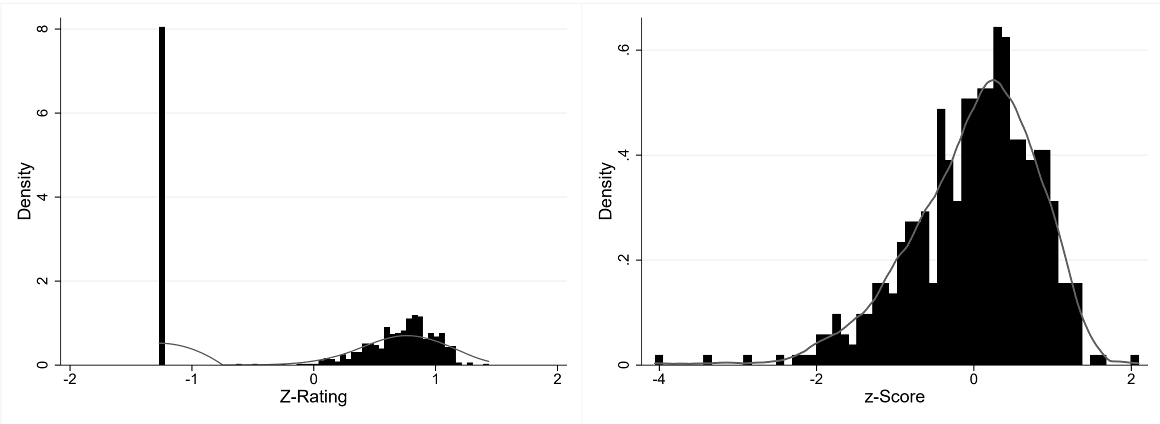
[8] The literature on crowdfunding suggests that entrepreneurial campaigns (i.e., successful) provide a reduction of demand uncertainty. See Cornelli (1996), and Ellman and Hurkens (2019).

early-stage venture sample. First, I focus on the first four applications round years between 2015 and 2018. This first restriction excludes 33.1 percent of observations. This sample restriction allows us to track venture outcomes at least one year after the crowd evaluation for my estimates of the signal effect. Finally, I exclude ventures registered on the platform, where the project is not receiving any evaluation from the users' community, leaving us with 506 observations. My estimates focus on the signal effect of the crowd-rating on venture subsequent performances, therefore project without evaluation is not informative, suggesting non-attractiveness for this sub-sample and is not on the scope of this chapter. Data from these four round applications allow observe ventures and their ex-ante characteristics at an earlier stage than prior studies, with higher granularity[9]. Unlike related literature on entrepreneurial finance that relies on administrative and commercial databases, my primary sample enables track ex-ante characteristics (i.e., founders) for ideas, ventures' products, or services that are unreported in the absence of financing event (Howell, 2019).

Scores. The data include 506 evaluations resulting in an average of the following seven questions answered by each evaluator: *success*, *usefulness*, *originality*, *ambitiousness*, *feasibility*, *affection*, and *societal and environmental impact* (see Appendix B for further details on the scoring process.). I focus my analysis on the average crowd-rating but I have also access to scores for all criteria, which I use only on additional specification. The nominal score ranges from 0 to 10, the higher nominal score is better, suggesting the quality of the project conditional on observables characteristics. Because of the crowd-rating variation (i.e., a standard deviation of 1.015) across round applications and for ease of interpretation, I follow prior studies and transform the nominal average score. I use a standardized *z-score* by normalizing the nominal score from each crowd evaluation to have mean zero and standard deviation one. The z-score indicates, for a given nominal score, how many standard deviations you are from the sample mean. The correlation between this standardized and nominal score is 0.99 (see Appendix Figure 3.A.1), and my results are robust to this transformation.

Ventures. The primary sample match project application information to complementary information on founders and financing events. However, tracking venture performances is challenging because many projects are not incorporated into administrative databases and occur recently (Kerr et al., 2014; Gonzalez-Uribe and Leatherbee, 2018; Howell, 2019). In

[9]For example, approximately 50 percent of my primary sample includes only ideas and are not structured into a registered firm in administrative database. This represents both a data collection and empirical challenge for this chapter, for which I do not observe the project or venture from official administrative sources.



(a) *z-Score* **(b)** *z-Score*

Figure 3.2 – Distribution of the Standardized Score.

Notes: This figure presents the standardized score (i.e., z-score) for the aggregated score from the crowd. Panel A shows the distribution of the standardized score for all projects with and without evaluation. Panel B shows the distribution for projects with at least one evaluation from the crowd.

addition, the online platform did not collect additional venture information after round applications leaving me without ex-ante characteristics. To deal with this challenge, I hand-collected additional information from several websites for each project. First, I obtain founders' characteristics from LinkedIn, which contains information on age, gender, education level, and the number of jobs[10]. I also collect information on the number of employees for incorporated ventures. Second, financing events are obtained from Dealroom, a commercial database spanning 2015-2019[11]. Dealroom records the french ecosystem from seed to late growth, comprising 14,162 ventures by January 2020. The financing events are linked to project characteristics using startups names, by carefully account for mismatch across project and startup name and changes over time. From these two web sources, I can match almost all venture characteristics to their project information contained on the platform[12]. Finally, I obtained Web traffic data from SimilarWeb. Web traffic records are available for 206 ventures in the first period after the project's applications and 180 ventures two periods after. As noted by Kerr et al. (2014), Web traffic is submitted to bias measurement because its level depends on characteristics and business model of ventures, as well as website data, could remain not to record by SimilarWeb until minimum traffic or they have launched a product. Round applications spanning 2015-2018, I collected

[10] I collect information only on public profiles based on web search and complement with AngelList profiles when LinkedIn data are missing. However, most of the founders are not registered on AngelList platform

[11] Related literature often relies on Crunchbase to measure financing events (e.g., Dalle et al. 2017), however, this data source poorly covers my sample of french early-stage ventures.

[12] For example, the minimum match rate for the founders' characteristics is 74.3 percent and 88.8 percent for financing events.

additional information at one and two follow-up years after application and evaluation. I match these three datasets to my primary sample and remove identifiers for the rest of the analysis.

2.3 *Variable Definitions and Summary Statistics*

In this section, I briefly define the main variables that I use in my analysis and present summary statistics. Appendix B provides additional information on variable definitions.

Financing Events. I primary measure of financing event is a binary indicator for subsequent external financing from early-stage investors. I restricted my measure to angels and venture capitalists round and corresponds to a period as of one and two years after the evaluation process, which I label Angel/VC at One and Two Years respectively. I use angels and venture capitalists round that characterize early-stage investors and excluded debt financing (i.e., household debt, bank debt, and non-bank debt) as well as external equity from the sample. I also observe funding amounts and investors' numbers but are not available for each event. Because I do not observe the funding amount for each event, I use this venture outcome as an illustration and rely on binary indicators.

Ventures Outcomes. I define three additional variables to measure venture success: venture survival, employment, and traction. Venture survival is defined as a binary indicator for ventures that survive as one and two years after the evaluation process. I carefully cross-checked this measure through several data sources. First, for incorporated ventures, I control their operating status on the official register of commerce. Second, for early-stage ventures not incorporated I identify employees' status on LinkedIn because of founder and employees register themselves as working for the venture (Howell, 2019). Finally, I control for the existence of a website. However, this source of information is not accurate because a failed venture could have an active website a long-standing after closure.

The second measure of venture success is a binary indicator for whether the venture has at least one employee. As for financing and survival, I measure this variable as one and two years after the evaluation process. In years where venture has no employee, in addition to founder team, venture employment is coded as zero. For failed ventures, I also code employment status as zero. I rely on a binary indicator because for many ventures I cannot identify exact employment levels, reducing missing data and measurement errors.

Finally, tracking venture success measures, such as sales or operating revenue, is challenging for early-stage firms, therefore I use website traffic records to measure venture's traction. Web flow is defined for an existing website as the yearly average of web traffic. In years where a venture failed, web flow is coded as zero. This variable is winsorized at the ninety-ninth percentile. Winsorizing allows us to remove the influence of outliers as well as measurement errors that can occur because of the data construction[13].

Founders. Using data from project application and LinkedIn, I obtain data on founders' characteristics. For each project, I identify founders that claimed to participate in the application time. I measure founder age based on birth date as reported on the register of commerce when is available. For founders without birth date available, birth date is defined as the high school graduation year less 18. I assign gender based on founder name, which is coded to one for male and zero for women[14]. At the year of application, I define whether founders members are still a student (i.e., first-time entrepreneur) or employed and the total number of jobs based on founders' claims. Finally, I measure graduation degree using four categories: MBA/Master, Ph.D., Engineering degree, and Undergraduate education that correspond to the highest educational level. If no graduation degree was found in LinkedIn profiles, I search from other public data sources.

Summary Statistics. Table 3.1 presents summary statistics for application round (Panel A), startup outcomes (Panel B), venture characteristics (Panel C), and founder characteristics (Panel D) in my analysis sample. Overall, my sample consists of four round spanning 2015-2018, with 500 project applications. Within the four rounds, the average number of evaluators is 12. Appendix Figure 3.A.3 maps the sum of ventures that launched a project on the online platform for the french official statistical areas at the department level. The maps are colored on a single scale: yellow colors represent french areas with the lowest of projects while dark blue colors represent areas with the highest level of project applications. Ventures that launched a project on the platform vary substantially across areas. Overall, 63 percent are localized in Ile-de-France, among them, 232 ventures are in Paris at the time of application round. Outside the Ile-de-France area, I identify 7 areas that have on average 10 projects. The geographic patterns are largely consistent with the startups' population localized in France.

The average aggregate score is 7.26 and ranges from 2.42 and 9.85. Among my

[13]Winsorize data at the ninety-ninth percentile assigned for any observations with values above this sample threshold the ninety-ninth percentile value. The website records sample shows a skewed distribution. Thus, winsorizing can reduce estimated bias with minimizing mean squared error when estimating means (Rivest, 1994).

[14]In contrast to related literature that assigns gender-name by using an algorithm, I code graduation degree by hand avoiding misspecification. All founders are assigned gender.

Table 3.1 – Summary Statistics

	N	Mean	Std.	Min	Max
Panel A. Application Rounds					
#Round	4				
Launch Month	12	6.38			
Launch Day	31	15.75			
#Upvoters	500	12.33	15.22	1	99
Score	500	7.26	1.01	2.42	9.85
Panel B. Startup Outcomes					
Prior Financing Round	466	0.17	0.37		
Prior Deal Round (€, 000)	450	51,7	260,4	0	3,000
Raise Angel/VC at One Year	500	0.07	0.25		
Deal Round at One Year (€, 000)	500	34,5	206,4	0	2,800
Raise Angel/VC at Two Years	347	0.04	0.19		
Deal Round at One Year (€, 000)	347	49,5	373,7	0	5,000
Startup Survival at One Year	467	0.85	0.34		
Startup Survival at Two Years	323	0.75	0.43		
Has One Employee at One Year	453	0.48	0.50		
Has One Employee at Two Years	312	0.44	0.49		
#Web Flow at One Year	206	8,230.76	23,397.85	0	158,333.3
#Web Flow at Two Years	180	13,379.09	55,954.93	0	438,650.5
Panel C. Startup Characteristics at Application Round					
Age (years)	468	1.98	8.00	0	170
Incorporated	500	0.51	0.50		
Incubator/Accelerator	468	0.38	0.48		
Has a Website	470	0.82	0.37		
#Word Pitch	498	151.97	98.56	0	839
VC Hub	500	0.41	0.49		
B2B Market	500	0.26	0.45		
B2C Market	500	0.46	0.49		
B2B/B2C Market	500	0.15	0.35		
Panel D. Founder Characteristics at Application Round					
#Founders	500	1.53	0.90	1	5
Age (years)	465	34.70	10.17	19	71
Male	468	0.71	0.45		
Female	468	0.29	0.45		
Serial Entrepreneur	462	0.26	0.44		
#Jobs	453	4.72	2.38	0	17
#Jobs before Round	453	3.79	2.39	0	17
Student	462	0.11	0.31		
Has a MBA/Master Degree	455	0.60	0.48		
Has PhD Degree	376	0.05	0.21		
Has Engineering Degree	386	0.16	0.37		

Notes: This table presents summary statistics for the application process (Panel A), venture outcomes (Panel B), venture characteristics (Panel C), and founder characteristics (Panel D). N=500. For each binary indicator, I show the mean and standard deviation. For continuous characteristics, I show the mean, standard deviation, minimum and maximum. In Panel D, I show only summary statistics for one founder for readability.

sample, the average financing likelihood is 7 percent and 4 percent as of one and two years after the evaluation occurring on the platform, respectively. The average deal amount is €569,000 and €1,7 million as of one and two years after, respectively. Appendix Table 3.A.2 provides additional details on financing by year spanning 2015-2019. The average survival rate is 85 percent and 75 at one and two years, respectively following the evaluation process, which represents a high short-term rate of venture success. The average rate of ventures with at least one employee in addition to the founders' team is 48 and 44 percent as of one and two years after the evaluation. For the sub-sample of ventures without missing data for website traffic (i.e., 41.2 and 36 percent of ventures), the average yearly traffic is 8,200 and 13,300 visitors as of one and two years. However, the sample distribution is highly skewed. For example, one year after the evaluation process the average yearly traffic ranges from 0 to 158,000 visitors.

At the application rounds, ventures are on average 1.98 years old, and 51 percent are incorporated at the registry of commerce. Overall, 38 percent of the 500 ventures (i.e., projects) have attended incubator and accelerator programs, and 41 percent of them are in a VC hub that corresponds to the concentrated geographical distribution of my analysis sample. On the 500 ventures, 26 percent are positioned on a B2B business model, another 46 percent on a B2C business model and 15 percent of ventures are positioned on a mixed model (i.e., B2B and B2C).

Ventures have on average 1.5 founders. The founder's average age is 34 years old, among them, 71 percent are men[15]. Overall, 26 percent of the project main founder is a serial entrepreneur. Another 11 percent are students at the application level. Finally, 60 percent have an MBA or a Master's degree.

2.4 *Sample Representiveness*

One concern about my analysis sample is the representativeness of early-stage ventures compared to the french start-up ecosystem and related literature, raising potential generalization concerns of my main findings (Bernstein et al., 2017). However, related data and evidence on early-stage ventures prior to fundraising events are rare, raising the difficulty to assess the representativeness of ventures launched on the online platform.

To assess the representativeness of my analysis sample to broader french ventures,

[15]Panel D of Table 3.1 reports founder characteristics at the application round level for the main founder. Team composition ranges from 1 to 5 founders. Additional summary statistics on the remaining founders are reported in Appendix Table

Appendix Table 3.A.3 compares by year and sectors, the 500 ventures (or projects) to a sample of ventures that raised funds derived from Dealroom. This sample consists of 3,945 french startups raising external funds spanning 2015-2018. I classify ventures into three groups based on the ventures-sector share: *(i)* similar, *(ii)* lower, and *(iii)* a larger share of ventures in my analysis sample[16]. Overall, 9 of the 17 sectors have a similar share than the french startups raising external funds, in particular for the electronics, food, and travel technologies. Another 3 sectors are slightly overrepresented in my analysis sample: the Art/Entertainment/Gaming sector (8 versus 5 percent), the CleanTech sector (8.6 versus 1.9 percent), and the Fashion sector (9.8 versus 2.2 percent). Finally, 5 sectors are underrepresented compare to the french startups share. Communication/Marketing and HealtTech sectors are particularly skewed, representing only 3.6 and 4.8 percent of my ventures, respectively.

Next, I compare venture and founder characteristics at the application round to related literature. On average the venture age is 1.9 years, which is comparable to the competition ventures in Howell (2019). Ventures have a lower participation rate into incubator or accelerator program (38 versus 57 percent), in the number of founders (1.5 versus 2.6), and prior funding (17 versus 47 percent) than ventures from AngelList in Bernstein et al. (2017). The incorporation rate is 51 percent, which is slightly higher to the 44 percent in Howell (2019). Overall, my analysis sample is similar both on sectors representativeness and venture characteristics than french startups ecosystem but also then related literature on early-stage ventures in the U.S. context.

Appendix Figure 3.A.4 shows the venture capitalist investment trends in France by the round stage. In 2014, there have been a total of 797 million dollars of investments from VC that encompass all rounds. This amount has increased over time, reaching 1.8 billion dollars in 2018. This 126 percent increase is primarily due to the number of deals over time, with an increase of 58 percent. This pattern is drive by an increase in the seed and early-stage investments while late-stage that increase only by 10 percent between 2014 and 2018. Comparing France to the U.S and the United Kingdom, the U.S appears as an outlier[17]. Overall, investments outperform by far, reaching 113 billion dollars in 2018 but have slightly increased over time, with an increase of 71 percent. In contrast, the figure shows that the U.S's investment amount is concentrated in the early and late stages. For example, the yearly total investment amount in early-stage is 39 and 69 billion dollars in late-stage for 2018. The difference between France and the U.S is the source of funds.

[16] For brevity, I pooled ventures share for all years in my sample.

[17] The U.S investment amount is 62 times higher than in France, needed a separate axis in the figure for the U.S.

A recent Mazars (2019) report documents that almost 93 percent of early-stage ventures rely on personal funds. This considerably contrasts with VC investments of 3 percent[18]. Because of this smaller interest for VC, this could be an explanation of the difference in VC investment amount over time.

3 A Signal Extraction Problem

There is a great debate among academics and investors on investment decisions and the screening process that motivated their selection. Entrepreneurs and startups' projects are highly uncertain about how they generate high-quality investment opportunities for early-stage investors. Investors rely on a multi-stage selection process (i.e., deal funnel process), starting from a hundred proposals to funded a very small number of projects (Gompers et al., 2020).

In this section, I develop a signal extraction model following the setups in Phelps (1972) and Aigner and Cain (1977), in which potential investors observe aggregate evaluations from platform users, and use this information to form investment decision[19].

3.1 *Model*

Entrepreneur (Startups).— Consider an entrepreneur or a startup that has a project (i.e., product) with a latent technology η. The entrepreneur launched his project on the platform to receive evaluations, feedback, and signal project's quality from potential investors. $\eta = \mu + \varepsilon$ can be considered as the project's net present value (NPV), but is hidden, where $\mu \sim \mathcal{N}(\bar{\mu},\ 1/\tau_\mu)$ is the baseline project's characteristics with mean $\bar{\mu}$ and precision $\tau_\mu = 1/\sigma_\mu^2 > 0$. $\varepsilon \sim \mathcal{N}(0,\ 1/\tau_\varepsilon)$ is a independent random shock with precision τ_ε.

Investors.— Consider a set of potential investors that observed the project's evaluation from the platform. For simplicity, there is a continuum of potential investors θ_i with total mass $\forall_i$, θ_i equal to one. Potential investors are interested in evaluating the project's

[18]Note that in France, VC investments are supported by government agencies that founded public funds that target early-stage ventures (OECD, 2019).

[19]Discrimination models are divided into tasted-based and statistical discrimination models (Bohren et al., 2019). However, in a taste-based model of discrimination (Becker, 1957), early-stage investors have non-financial preferences for a particular group, discrimination is purely caused by a taste or preference against a group with specific observable characteristics, using these characteristics as a proxy for venture quality. In contrast, my conceptual framework relies on the literature on signaling in entrepreneurial finance (e.g., Tian and Wang 2014), involving discrimination caused by a purely financial utility.

profitability and decide whether to invest in the project.

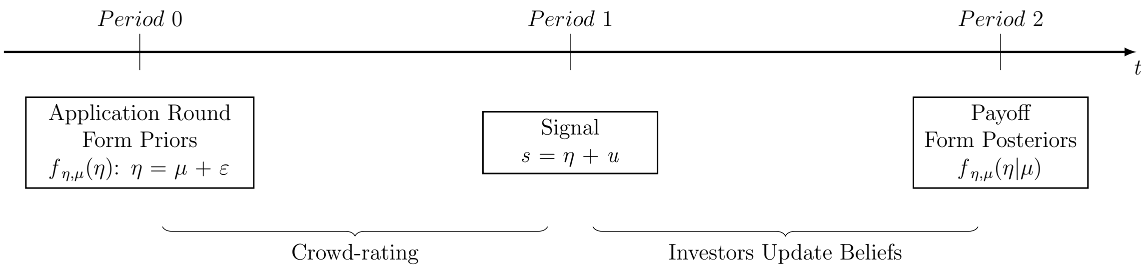


Figure 3.3 – Timeline of the Signal Extraction.

Note: This figure shows the evaluation and signal diffusion to potential early-stage investors.

Evaluations and Signal.— Entrepreneur launch a project on the platform. The crowd (i.e., platform's users) evaluate each project without history and few assets, resulting in an aggregate rating. In this framework, information about project profitability is modeled as a noisy Gaussian signal arriving after the crowd-rating and observed by the continuum of potential investors. Specifically, there are three time periods $t \in \{0; 1; 2\}$. In period 0, potential investors form prior belief according to baseline project's characteristics η. In period 1, the crowd-rating generates a noisy signal observed by potential investors and they updated their beliefs on the project's profitability according to the signal in a naïve Bayesian form. In period 2, potential investors maximize their expected payoff with respect to their posterior belief about profitability.

Thus, in period 1 potential investors observe a noisy signal $s = \eta + u$ of the profitability, where $u \sim \mathcal{N}(0, 1/\tau_u)$ is an independent random shock with precision τ_u. Higher uncertainty in the project's profitability suggests lower signal precision τ_u. Following Bohren et al. (2019), the signal precision can be interpreted as the amount of subjectivity in investors' judgment involved in the crowd evaluation and belief in the observed signal. Potential investors do not observe the true profitability but incorporate the signal s to form the posterior belief of expected profitability conditional to the signal. Given prior belief $f_{\eta,\mu}(\eta)$ and signal distribution, investors estimate:

$$\mathrm{E}(\eta|s) = (1-\gamma)\bar{\mu} + \gamma s \tag{3.1}$$

where $\gamma = \frac{\tau_\eta}{\tau_\eta + \tau_u}$ is the relative precision of the signal. If the signal is extremely noisy, then potential investors place more weight on the baseline project's characteristics $\bar{\mu}$ while if the signal is objective (i.e., precise) $s \to \infty$, potential investors place more weight on the signal.

Proposition 1. *The crowd evaluation mitigates information asymmetries between entrepreneurs and potential investors, revealing information.*

The evaluation from the platform's users produces a signal observed by potential investors, updating their prior belief on the profitability of entrepreneur's project. Therefore, uncertainty and information frictions are reduced between entrepreneurs and investors.

Assuming that the conditional signal $s \mid \eta \sim \mathcal{N}(\bar{\mu},\, 1/\tau_\eta)$, the posterior belief about profitability conditional on observing the signal s is also normally distributed:

$$f_{\eta,\mu}(\eta|s) \sim \mathcal{N}((1-\gamma)\bar{\mu} + \gamma s, \frac{1}{\tau_\eta + \tau_u}) \tag{3.2}$$

Lemma 1: *If η is normally distributed, then the expectation of η conditional on the signal s can be written:*

$$\begin{aligned} \mathrm{E}(\eta|s) &= \Phi\left(\frac{\mathrm{E}(\eta|s)}{\sqrt{1+\mathrm{Var}(\eta|s)}}\right) \\ &= \Phi\left(\frac{\tau_u\bar{\mu} + \tau_\eta s}{\sqrt{(\tau_\eta + \tau_u)(1 + (\tau_\eta + \tau_u))}}\right) \end{aligned} \tag{3.3}$$

where Φ is the cumulative density function $(c.d.f)$ of the standard normal distribution.

Investment Decision.— Early-stage investors provide an important source of financing for entrepreneurs that might have difficulty in attracting financing (Kaplan and Stromberg, 2001; Gompers and Lerner, 2001). However, entrepreneurs' ideas are difficult to finance because of uncertainty and information asymmetries, resulting in risky investment with payoff less than the project NPV. Given the posterior belief (2), potential investors decide whether to invest in the entrepreneur's project if investors' maximize their expected payoff $x \in \mathbb{R}$ conditional on posterior belief:

$$\begin{aligned} Investment &= \arg\max_{\eta} \mathrm{E}(\eta - x|s) \\ &= (NPV|s > 0) \end{aligned} \tag{3.4}$$

Note that potential investors are heterogeneous and differ in their prior belief $f_{\eta,\mu}(\eta)$, thus, potential investors decide to invest in the project if and only if $\mathrm{E}(\eta \mid \mathrm{s}) \geq x$. Using (3), investment decision can be written as follows:

$$\Phi\left(\frac{\tau_u\bar{\mu}+\tau_\eta s}{\sqrt{(\tau_\eta+\tau_u)(1+(\tau_\eta+\tau_u)}}\right)-x>0 \tag{3.5}$$

Given that potential investors maximize their expected payoff, the investment decision is increasing on baseline characteristics $\bar{\mu}$ and the signal s. To see this, note that the effect of the signal from crowd evaluation on investment decision is given by:

$$\frac{\partial Investment}{\partial s}=\phi\left(\frac{\tau_u\bar{\mu}+\tau_\eta s}{\sqrt{(\tau_\eta+\tau_u)(1+(\tau_\eta+\tau_u))}}\right)\times\frac{\tau_\eta}{\sqrt{(\tau_\eta+\tau_u)(1+(\tau_\eta+\tau_u))}}>0 \tag{3.6}$$

where ϕ is the probability density function ($p.d.f$) of the standard normal distribution. Since the Gaussian $p.d.f$ is strictly increasing for any random variable, therefore the effect is positive and increases according to the signal.

Suppose now that investment decision is binary, such as $Investment \in \{0\ ;\ 1\}$, and potential investors maximize their expected payoff as before. In this framework, the investment decision is characterized by a cut-off rule that depends on the signal (i.e., if potential investors observed a sufficiently optimistic signal). The conditional density of the signal $f_{s|\eta}$ according to the profitability satisfies the monotone likelihood ratio property, the conditional expected payoff is strictly increasing in s.

$$\Phi\left(\frac{\tau_u\bar{\mu}+\tau_\eta s}{\sqrt{(\tau_\eta+\tau_u)(1+(\tau_\eta+\tau_u)}}\right)\geq x \tag{3.7}$$

$$s^*\geq\frac{\Phi^{-1}(x)\times\sqrt{(\tau_\eta+\tau_u)(1+(\tau_\eta+\tau_u)}-\tau_\mu\bar{\mu}}{\tau_\eta} \tag{3.8}$$

$$s^*\geq\frac{\Phi^{-1}(x)\times\sqrt{(\varpi)(1+\varpi)}-\tau_\mu\bar{\mu}}{\tau_\eta} \tag{3.9}$$

where $\varpi=(\tau_\eta+\tau_u)$. Consequently, the investment decision is characterized by a cut-off rule s^*, increasing in x and decreasing in $\bar{\mu}$.

Proposition 2. *The investment decision is increasing on the effect of the signal (i.e.,* $\frac{\partial Investment}{\partial s}>0$*) obtained from the crowd evaluation.*

If potential investors share the same prior belief on the project's profitability, the signal provides more precise information about the profitability, and the baseline characteristics belief is reduced.

Discussion of the Model. My extraction signal framework implies several plausible mechanisms that could explain the signaling effect of the crowd evaluation. In the rest of this section, I discuss several features of the model.
Early-stage investors could be uncertain over the crowd evaluation and the signal quality, involving subjectivity in judgment (Bohren et al., 2019). In my conceptual framework, the subjectivity in judgment corresponds to the signal precision $s \to \infty$. Therefore, higher subjectivity that could arise from uncertainty in the evaluation process (i.e., uncertainty about the crowd or noisy information on observable characteristics), decreasing the precision of the signal (Kelley, 1973). Subjectivity relies on stereotypic bias. Therefore, evaluators place more weight on group statistics, increasing discrimination from belief-based (i.e., prior-beliefs in period 0). For example, early-stage investors' decisions can be driven by stereotypes, such as gender or universities (Ewens and Townsend, 2020; Bordalo et al., 2016). In contrast, as objectivity increases, the signal precision arising from the evaluation process increases about venture quality.

Early-stage investors, as well as evaluators, which hold appropriate beliefs about aggregate group differences, fall into a statistical discrimination framework (Phelps, 1972). Statistical discrimination can be explained by rational expectations, where evaluators in period 0 form prior beliefs about projects' quality that differ by aggregate group characteristics, inferring individual quality based on these group statistics (Aigner and Cain, 1977; Altonji and Pierret, 2001). For example, evaluators can perceive certain group observable characteristics as higher, using these characteristics as a proxy for venture quality to infer screening of NPV. However, early-stage investors and evaluators can hold miscalibrated beliefs, which involve incorrect beliefs about group statistics. Miscalibrated beliefs appear from incorrect stereotypes of venture quality (Bordalo et al., 2016). Although this miscalibration can be made unconsciously by both evaluators and investors. This underlying mechanism is modeled by incorrect prior beliefs $\bar{\mu}$ about observable venture characteristics as a proxy for profitability.

Finally, the crowd evaluation could experience a false consensus effect (Ross et al., 1977). The false consensus effect implies that evaluators have heterogeneous beliefs - rational and miscalibrated - about average quality. For example, evaluators could infer information on venture quality from incorrect beliefs that introduce bias, while other evaluators form correct beliefs conditional to baseline project's characteristics (Bohren et al., 2019). However, as mentioned prior, evaluators with incorrect beliefs could are implicitly not aware of them. Thus, these evaluators may believe that other evaluators use the same discrimination against some group statistics based on incorrect beliefs.

4 Identification Strategy

This section describes the main identification strategy which is relied on to my stylized model of the signal extraction. I begin by describing the identification strategy for estimating the effect of crowd evaluation on investors' subsequent decisions, and how the evaluation is useful to reveal information related to uncertain projects. Then I discuss the identifying assumptions that could affect my estimates.

4.1 *Empirical Strategy*

The empirical strategy aims to identify the signaling effect resulting from crowd evaluation for a population of startups. Information frictions are particularly severe for startups, increasing uncertainty about the project's quality among early-stage investors. The standard approach to select early-stage ventures is to rely on evaluation panels in the context of business plan competitions to score proposals (McKenzie and Sansone, 2019; Howell, 2019). However, human judgment can be time-consuming and costly to predict success. Therefore new forms of evaluation on an internet platform could provide information efficiently.

I assume that the investment decision (η - x) to a project reflects baseline observable characteristics ($\bar{\mu}$) and the signal s[20]. Combining equations (1) and (3), the early-stage investor expectation profitability conditional to the signal (i.e., the crowd evaluation) is, therefore[21]:

$$E[Y|\eta, s] = Y_{i,t+\Delta t} = \beta_0 + \beta_1 z\text{-}Score_i + \delta \mathbf{X}_i^{'} + \gamma_t + \varepsilon_i \tag{3.10}$$

where the outcome variable $Y_{i,t+\Delta t}$ is an indicator variable that equals one if the project received financing from business angels and venture capitalists, and zero otherwise[22]. X_i is a set of time-invariant observable characteristics for the founding team and project including venture age, the incorporation status, whether the startup received prior external funding before the application round, whether the startup participated in incubator or accelerator program, the presence of an active website, the number of

[20] Assuming this relation, early-stage investors decide whether to invest conditional on the prior mean of quality and the observed noisy signal.

[21] I use notation E[.] that describes regression results through a linear conditional expectation estimator.

[22] As mentioned in Section 2, my outcome variable measures the project's success between one and two years since the application round, that allows us to track performances into the short-term and longer-time Catalini et al. (2019).

founders, sector indicator variables, and the number of upvoters[23]. γ_t are time fixed effects controlling for different round applications (i.e., absorbing the year of project and evaluation). Standard errors are clustered at the project level i to control for any serial correlation across applicants (Wooldridge, 2010).

The coefficient of interest is the *z-Score* which captures in terms of standard deviations, a given absolute score falls relative to the sample mean. This measures the impact of crowd evaluation on subsequent financing events, with a higher *z-Score* suggesting a higher project quality. Under the assumption that the signal is objective and with Bayesian estimates that incorporate prior information on observable characteristics X_i this measures the impact of crowd evaluation on financing events, with a higher *z-Score* suggesting a higher project quality.

Potential investors observe a noisy signal resulting from an aggregate rating and the number of upvoters that reflect project quality and profitability. However, OLS estimates[24] of equation (10) could be biased because crowd-rating is endogenous and potentially correlated with the error term ε. The ideal experiment would have to estimate each crowd-rating on financing events through a source of quasi-experimental variation at the project level but is outside of this chapter. Instead, I develop several arguments build on prior literature to recover a consistent estimate of the coefficient β_1.

A first concern is that omitted variables could upward bias estimates by both influencing the aggregate crowd-rating and the financing event. A large number of factors potentially determine the number of upvoters at the end of the application round[25], and hence the aggregate information about the crowd-rating, which are external shocks independent of the project's quality. For example, the number of upvoters not only depends on the project's characteristics, but also on the number of project applications on the online platform varying by year, month and day, and with respect to the number of upvoters that are connected on the platform. In addition, interest from the crowd can also depend on factors the sectors and the stage of development. Appendix Figure 3.A.1 highlights an important variation according to the launched date and stage of development of the project. Another concern is the absence of project fixed effects for startups that capture unobservable characteristics reflecting quality and NPV. Introducing individual

[23]In my baseline specification, I estimate the relationship between financing events and the standardized score without observable characteristics, and then control in following specifications.

[24]My main outcomes are a binary indicator, I estimate equation (10) by a linear probability model (LPM).

[25]Note that, in my sample, I do not observe at every point in time the aggregate nominal score resulting from the crowd evaluation.

fixed effects in this specification would require to track observable characteristics as well as outcomes over time (i.e., introducing within-variation). However, my sample does not record information before the launched date on the online platform[26].

To address this concern, I estimate the causal effect of the crowd evaluation using an instrumental variable strategy, where I instrument for the crowd-rating with a measure of a quasi-randomly assigned evaluator to score a project. In this specification, differences in the outcomes are that some evaluators are more lenient than others in scoring projects, their leniency creates exogenous variation in the overall score. In this identification strategy, I estimate the local average treatment effect (LATE)[27].

Instrumental Variable. I construct my instrument that measures the cumulative evaluator leniency that accounts for generosity when scoring other projects following Chen (2018) and Farronato et al. (2020)[28]. For evaluator i scoring project j by year t, and let denote n_{jt} the set of evaluators for project j in the year t. Let $k \in K_{jt}$ an evaluator that evaluate project j. Let s^k_{-j} the average scoring by the set of evaluators leaving out the data from project j. The average cumulative evaluator leniency of project j by year t is construct as follow:

$$EvaluatorLeniency_{ijt} = Z_{ijt} = \frac{1}{n_{jt}} \sum_{k \in K_{jt}} s^k_{-j} \tag{3.11}$$

The instrument is constructed on the individual standardized score, yielding an evaluator leniency measure that varies between average harshness and lenient evaluations. The evaluator leniency measure is constructed across all projects' development stages and technologies but I allow the instrument to vary across years in order to capture variation among evaluator assessment over time. This approach controls for differences across project characteristics and leniency of evaluators on the online platform. Including years' variation allows us to reduce the comparison of projects that have the probability to be assigned to the same set of evaluators because of the assignment in my setting is

[26] Note that only a small fraction (1%) of startups relaunch a project on the platform allowing to track startups over the time

[27] Note that in the linear instrumental variable identification with continuous treatment, without restricting heterogeneity in the first stage, the standard linear triangular system estimates a continuous version of the LATE as a weighted average of the derivatives of the relationship between the endogenous regressor and the instrument (Angrist et al., 2000). Therefore the point estimate β_1 is $\int_{\infty}^{0} E[g^{'}(z - Score, U).\omega] \, \mathrm{d}(z - Score)$ with ω the weighting function.

[28] Note that this instrumentation strategy is related to the leave-out judge leniency measure (i.e., residualized with fixed effects) used in the literature which estimates the effect of the criminal justice system, see for example Kling (2006) and Dobbie et al. (2018). However, my instrumentation strategy differs due to the use of non-residualized evaluator leniency measure.

not random as previous studies in the literature (e.g., Aizer and Doyle Jr 2015, Dahl et al. 2014). Thus, the instrument is the cumulative scoring propensity for a project of a quasi-randomly assigned evaluator relative to other evaluations in the same year. Using the leave-out measure is important in my setting because instrumenting the crowd-rating by the evaluator leniency without leaving out the data for venture or project i would bias my estimates of the causal impact of the score. In addition, the instrumental variable construction excluded project characteristics at the application round in order to allow an examination of the sensitivity of my estimates with and without these time-invariant controls.

The first and second stages of my instrumental strategy are given by:

$$z\text{-}Score_i = \alpha_0 + \alpha_1 EvaluatorLeniency_{ijt} + \delta \mathbf{X}_i^{'} + \gamma_t + \upsilon_i \tag{3.12}$$

and

$$Y_{i,t+\Delta t} = \beta_0 + \beta_1 \widehat{z\text{-}Score}_i + \nu \mathbf{X}_i^{'} + \gamma_t + \epsilon_i \tag{3.13}$$

where *Evaluator Leniency*$_{ijt}$ is the average cumulative evaluator leniency, $z - \widehat{Score}_i$ is the predicted standardized score, $X_i^{'}$ is a set of time-invariant observable characteristics. γ_t are time fixed effects controlling for different application rounds. Standard errors are clustered at the project level i. I perform two-stage least squares (2SLS) with equation (12) as the first stage and equation (13) the second stage. I estimates of β_1 capture any effects through only exogenous variation in the evaluator leniency described above that is independent of project variation in the baseline characteristics to identify the causal effect of the crowd-rating. The 2SLS estimates can be interpreted as continuous LATEs at the condition that the main coefficient of interest β_1 is random (Imbens and Angrist, 1994; Angrist et al., 2000). Consistent with this condition and with my settings, the standardized score of a project could depend on the likelihood of receiving a lower or higher score whose project could have assigned to a different set of evaluators.

The analysis sample includes 2,674 evaluators during the sample period of 2015-2018. On average, the number of evaluators that evaluate a project is 21, with the average active evaluator-by-year is 1,301. Appendix Figure 3.B.1 presents the distribution of the cumulative average evaluator leniency instrument for the standardized score. The evaluator leniency measure ranges from -1.47 to 0.73 with a mean of -0.38 and a standard deviation of 0.31, suggesting that the variation in leniency represents high differences in evaluators' propensity to score a project[29]. This figure provides also a graphical representation of the

[29] Note that projects could be evaluated by multiple evaluators. Thus, I average the average leniency

first-stage relationship between the standardized score and my evaluator leniency measure controlling for the application round fixed effects, with a histogram for the density of the evaluator leniency. This is analog to equation (12) in a flexible way, estimating a local linear regression of standardized score on my evaluator leniency measure (Dahl et al., 2014). The actual crowd-rating is monotonically increasing in evaluator leniency and approximately linear. Thus I use the variation in evaluator leniency to instrument for the standardized score from the crowd to identify the causal effect of crowd-rating for ventures whose overall scoring differ in evaluators' propensity to be lenient or harsh, maintaining the project quality constant[30].

4.2 *Identifying Assumptions*

To interpret these two-stage least squares estimates as the causal impact of the score from the crowd involves three conditions: *(i)* that evaluator leniency is predictive of the standardized score, *(ii)* the evaluator leniency would impact a venture's subsequent outcomes only through the scoring rate, and *(iii)* that projects evaluated by a lenient evaluator would also be evaluated by a harsh evaluator.

Appendix Table 3.B.2 reports the first-stage from specification (12). Point estimate in column (1) that controls only for the application round fixed effects suggests that the evaluator leniency measure is highly predictive of the standardized score from the crowd. Column (2) adds control for project application characteristics: age, incorporation status, whether ventures received prior external funding before the application process, whether ventures participated in incubator or accelerator programs, the presence of an active website, the number of founders, and the number of upvoters. Column (3) also adds additional controls: the count of words in the venture's pitch (i.e., in logarithm), the business model, whether ventures have a serial entrepreneur, a student, or women in the founding team. In column (2), I find a strong correlation between the two measures, suggesting that on average one standard deviation in the evaluator leniency measure increases the standardized score by 0.85. The crowd-rating does not increase one-for-one with my instrument but is highly predictive of the overall score in my settings. The findings are consistent with the visual evidence in Appendix Figure 3.B.1.

measure at the project level. At the evaluator level, the evaluator leniency measure ranges from -4.78 to 2.17, with a mean of -0.37 and a standard deviation of 0.67.

[30]Using the leave-out mean instrument, results could be biased because the evaluator assignment is not truly random in my setting, yielding potential selection. In robustness tests, I present estimates using the residualized measure of evaluator leniency and residualized measure that accounts for stage-by round fixed effects. These measures are a modified version of the Jackknife IV that uses evaluator fixed effects as instruments (Kling, 2006). Results are nearly identical across three different measures (see Appendix Table 3.B.7).

Finally, the impact of evaluator leniency measure on the crowd-rating is also highly statistically significant, with F statistics above the rule-of-thumb value of 10, reducing the concern that my results are subject to weak instrument bias (Stock and Yogo, 2005).[31]

A second concern with my causal interpretation of β_1 in equation (13) is that my evaluator leniency measure must be uncorrelated with observable and unobservable projects' characteristics. The exclusion restriction required for a valid instrument is that the evaluator leniency does not directly impact a venture's subsequent financing events or subsequent real venture outcomes, except through its impact on the current probability to received low or high ratings. This condition is likely to be satisfied. The setting has several advantages: *(i)* the evaluation process is centralized on the online platform and does not depend on whether ventures are located, and *(ii)* ventures cannot choose specific evaluator and each evaluator's scoring is not revealed to ventures. For example, ventures, evaluators, and early-stage investors only discover the aggregate score on the seven components and the aggregate score on the online platform, platform users can't take into account such leniency. Therefore, conditional on project characteristics the instrument should be as good as quasi-randomly assigned. However, the evaluation process is non-random in my settings, involving threats to identification that evaluator leniency correlates unobservable time-varying characteristics that affect venture outcomes.

While the exclusion restriction is directly untestable, I can partially test the quasi-random assignment of evaluators. First, I examine the sensitivity of the first-stage by comparing the estimated coefficient with the inclusion of a large set of observable characteristics. Under the null of quasi-randomly assigned evaluators, adding these control variables would do not significantly change the point estimates, as observable venture characteristics should be uncorrelated with evaluator leniency. In Appendix Table 3.B.2, including controls in columns (2-3) does not change the magnitude of the point estimates on the instrument, ranging from 0.850 to 0.867. This is consistent with the quasi-randomness of evaluators. Second, I examine whether the nonrandom variation in the evaluator leniency is unrelated to project baseline characteristics at the time of application that affects venture outcomes. To assess whether the evaluator leniency measure is unrelated along with observable characteristics, Appendix Table 3.B.1 empirically verifies that the evaluator's assignment is as good as random, conditional on

[31] I also test for weak instruments concern using robust F-statistic propose by Olea and Pflueger (2013). This F-statistic is robust to heteroscedasticity and serial correlation. In all specifications, my F statistics are above the adjusted critical value of 23.1 suggests by Olea and Pflueger (2013). For example, the first-stage F-statistic for subsequent financing events over the next year, including observable venture characteristics is 52.6.

application round fixed effects. The first column documents that ventures' age, a prior funding event, and the number of evaluators are highly predictive of the standardized score. Column (2) examines whether the evaluator leniency measure can be predicted by the same observable characteristics. The instrument is not statistically related to venture characteristics, except the number of founders that is statistically significant at the 5 percent level, but the variables are jointly not significant (p=0.24). I also test the balance of project characteristics across those that are related to generous or strict evaluators available on the online platform in a given year[32]. Appendix Table 3.B.2 reports the observable characteristics divided by quartiles of the instrument distributions, relative to the average for each application round. The rows show that project characteristics are similar across the quartiles. The incorporation status, whether ventures participated in incubator or accelerator programs, and whether ventures have an active website are particularly similar across the first and the fourth quartiles, suggesting that been assigned to a strict or lenient set of evaluator does not depend on observable characteristics. Only whether ventures are located in a VC hub and the number of upvoters, are statistically different from zero at the 10 percent level. Taking together, these results suggest that evaluators with high and low scoring propensities are assigned similarly at least among the observable venture characteristics.

However, I cannot rule out that unobservable variables affect subsequent venture outcomes because the observed evaluator leniency measure is not randomly assigned to a project. Therefore, the exclusion could also be violated. For example, in my setting, a lenient evaluator is attracted to projects with higher unobservable quality that determine both overall scoring and subsequent outcomes. In contrast, suppose that a strict evaluator would more likely to evaluate a project with low quality, thus observed evaluator leniency is correlated with unobserved quality. Finally, evaluator leniency could impact subsequent outcomes through feedback posts on the online platform. Therefore, challenges to my identification strategy come from additional channels associated with evaluator decision-making. However, the underlying assumption that evaluator impact outcomes only through the crowd-rating process is empirically untestable, and my causal estimates should be interpreted with these caveats in mind.

The final condition to interpret my estimates as the causal effect (i.e., continuous version of the LATE) is the monotonicity of evaluators' leniency. In my setting, the

[32]Following Doyle Jr et al. (2015), I divide into quartiles based on the average difference between evaluator leniency and the average leniency measure in the application rounds, in order to reflect the identification strategy. Note that my balancing test is nearly identical to dividing my instrument into quartiles.

monotonicity assumption is that projects evaluated by a set of strict evaluators would also be evaluated by set lenient evaluators, and similarly that projects evaluated by a lenient set of evaluators would also have been evaluated by a set of stricter evaluators. One testable implication of the monotonicity assumption is that the first stage estimates should be positive across subgroups. Appendix Tables 3.B.3 and 3.B.4 report the first stage estimates separately by project characteristics. I find that all point estimates are non-negative and similar to first stage results reported in Appendix Table 3.B.2, suggesting that evaluators scoring are similar across observable characteristics. My results are consistent with the monotonicity assumption.

5 Impacts of Crowd-Rating on Early-Stage Investors

This section describes the impact of crowd rating on subsequent financing conditional on baseline project characteristics and the role of signaling on early-stage investors. I begin by examining the relationship between score, venture subsequent financing, and observable characteristics. Then, I examine the informational effect of crowd-rating on early-stage investors.

5.1 *Baseline Statistics*

I consider the venture and founder characteristics that are observable on the platform at each project application, informing evaluators. I estimate the unconditional association between these characteristics and the standardized score, subsequent external financing both at one and two years after the evaluation process.

Column (1) in Appendix Table 3.B.1 reports the OLS estimates for the standardized score that includes application round fixed effects without controlling for the total number of upvoters for each project. The estimates show a strong negative correlation between the venture's age and the standardized score, suggesting that early-stage ventures received higher scores from the crowd. Having a higher number of upvoters is strongly associated with the standardized score, which could reflect both perceived quality and attractiveness. Prior financing event to the evaluation process is positively associated with a higher likelihood of a greater score, reflecting both venture's quality and a decrease of uncertainty on the likelihood of success. Attending an Incubator or Accelerator program is positively associated with the standardized score but is statistically insignificant at the 10 percent level. Surprisingly, being located in a VC hub state impacts negatively the score but statistically insignificant at conventional levels, which provides an opposite relationship with related literature in the US context (e.g., Howell 2019, Bernstein et al. 2016). The remaining columns (Column 2-3) report the linear probability estimates for subsequent financing events on observable characteristics including application round fixed effects. The number of upvoters remains highly significant with subsequent financing as of one year after the evaluation process but has no predictive impact at two years. This reflects that the crowd evaluation measures the short-term effect of interest from evaluators and potential early-stage investors. Similarly, the other observable characteristics are significantly different in subsequent financing events across time considered. For example, attending an Incubator or Accelerator program and having a website is positively associated with financing rounds at one year[33]. Prior financing round at the time of the project application is highly predictive of financing rounds at two years, but statistically insignificant at one year. Finally, venture age (or project age) has a differential impact according to the period, with a positive correlation at one year and a negative correlation at two years after the evaluation process.

5.2 *Signal Informativeness of the Crowd-rating*

In this section, I consider the impact of crowd-rating on subsequent financing events as outcomes. I begin my analysis by considering the evidence on Angel and VC funding rounds at one and two years with visual evidence. Appendix Figure 3.B.2 presents average financing events on the standardized score. I residualized financing events with respect to time-invariant characteristics, including round applications fixed effects. In Panel A, the figure shows a positive relationship, but small magnitude between raising Angel or VC funds at one year after the evaluation and the standardized score from the crowd. This suggests that projects having higher scores are more likely to be fund. This pattern is similar for subsequent financing events at two years (Panel B). This figure provides small evidence of score impacts on funding rounds.

To further explore the impact of the score as a signal of project quality on subsequent financing events, I turn to the regression in Table 3.2, using OLS and 2SLS estimates. I control for differential project applications and community of upvoters over time, and for the possibility that financing rounds could differ for different years by including application rounds fixed effects in all specifications.

Panel A of Table 3.2 presents the short-term impacts over the next year, and Panel B the impacts over the next two years. The OLS estimate in column (1) that controls

[33] For example, attend to an Incubator or Accelerator program increase by 6.8 percentage points the likelihood of financing as of one year after the evaluation. Similarly, a website increases by about 3.8 percentage points.

Table 3.2 – Crowd-Rating Impacts on Financing: OLS and 2SLS Results

Dependent Variable	Angel/VC			
	OLS		2SLS	
	(1)	**(2)**	**(3)**	**(4)**
Panel A. Impact at One Year				
z-Score	0.014	0.013	-0.043	-0.040
	(0.010)	(0.012)	(0.033)	(0.036)
Obs.	500	461	481	443
R^2	0.10	0.13	0.07	0.13
Mean Dependent Variable	0.07	0.075	0.07	0.076
Panel B. Impact at Two Years				
z-Score	0.009	0.001	-0.008	0.001
	(0.008)	(0.010)	(0.024)	(0.025)
Obs.	347	317	342	312
R^2	0.07	0.14	0.07	0.15
Mean Dependent Variable	0.04	0.04	0.04	0.041
Controls	No	Yes	No	Yes
Indicators for Application Round	Yes	Yes	Yes	Yes

Notes: This table presents the estimated coefficient β_1 from OLS and 2SLS of the impact of crowd-rating. The sample includes all projects that are evaluated from the crowd spanning 2015-2018. 2SLS specification instrument for crowd-rating using an evaluator leniency measure that is estimated using data from other evaluations evaluated by a platform's user in the same year. Outcomes in Panel A are an indicator equal to one when ventures experienced funding round over the next year (columns 1-4). In Panel B, outcomes are similar but measured over the next two years. All specifications control for application rounds fixed effects. Columns 2 and 4 add venture characteristics as control variables. Standard errors are clustered at the project level.

only for the application rounds fixed effects suggests that the crowd-rating is positively associated with the likelihood of subsequent financing over the next year, but is not statistically significant at conventional levels (p=0.117). As mentioned in Section IV.2, a confounding issue is that, with the respect that projects' attractiveness is positively related to the number of upvoters, the impact of crowd-rating could be biased. Therefore, I control for the total number of upvoters and for all observable venture characteristics to deal with endogeneity issues[34]. The OLS estimate in column (2) is very similar to the baseline specification without control but the magnitude falls, suggesting that baseline controls are important for addressing omitted variable bias. A one standard deviation increase in the standardized score experienced by a project at the application round thus increases the probability of funding round over the next year by 1.3 percentage points, relative to the probability of 7.5 percent. However, on average, the crowd-rating has

[34]For readability, I do not show estimated coefficients on all the control variables in all tables.

a small and insignificant impact on the likelihood to have made a deal with angels or venture capitalists as of one year after the application process (p=0.257).

The remaining columns (3-4) report the 2SLS estimates by exploiting plausibly exogenous variation in cumulative evaluator leniency[35]. In contrast to OLS estimates, I find a negative impact in the short-run. Both with and without observable venture characteristics, my 2SLS estimates suggest no impact of the score from the crowd on the likelihood of subsequent financing events as of one year after the application process. The estimates are small and precise enough (a 95% confidence interval ranging from -0.11 to 0.03) to support the conclusion that the crowd had no effect. The extreme of the 95% confidence interval allows for an increase of the probability as a result of one standard deviation in the standardized score of financing of 3 percentage points. I now turn to the impacts over the next two years. Only about 4 percent of projects experienced subsequent financing events as of two years after the evaluation process. In OLS specifications (columns 1-2), I find a small and positive impact on the likelihood of funding rounds conditional on observable characteristics (0.001, s.e.=0.025), but statistically indistinguishable to zero. Similar patterns emerge with my 2SLS estimates (columns 3-4). I find no detectable impact on subsequent financing deals over the next two years, but less precisely estimated than OLS.

In contrast, the estimated coefficient for the number of upvoters is positive and statistically significant at 5 percent level. For example, the point estimate in column (4) suggests that a one percent change in the log number of upvoters (with a mean of 2.06 and s.d.=0.98) would result in a 0.039 unit increase in the probability of raising external funds from early-stage investors over the next year. The estimated impact of the number of upvoters on the probability of subsequent financing events is small in magnitude, but suggests that the number of upvoters reflects evaluators and potential early-stage investors interest's in the project and captures information (Bernstein et al., 2017)[36].
Taking together, these results suggest that the aggregate rating from the crowd is not able to identify high growth potential ventures conditional on ex-ante characteristics, which is consistent with visual evidence present in Appendix Figure 3.B.2. Thus, the evaluation process did not provide information to potential early-stage investors, invalidating my

[35] Appendix Table 3.B.6 presents the reduced form results from OLS. The reduced form results are highly similar to the 2SLS results, which is consistent with the strong first-stage estimates between the evaluator leniency measure for other projects and the venture's notation. Also, to the extent that the exclusion restriction is violated, the reduced-form estimates can be interpreted as the causal impacts of being assigned to a lenient or more strict set of evaluators.

[36] Appendix Table 3.B.1 examines the value of evaluators and potential early-stage investors by estimating the number of upvoters on subsequent financing rounds. The estimated interest for the probability of financing over the next year is 0.021 (s.e.=0.013) and 0.016 (s.e.=0.009) over the next two years, suggesting a positive short-term predictor for real outcomes.

proposition 1 summarizes in my conceptual framework.

So far, I have focused on whether the aggregate score revealed information to early-stage investors. However, crowd-rating has seven components, which might signal differently projects' quality. Table 3.3 presents estimates from OLS specification (10) for my seven components of the aggregated score. Each component is a standardized score of the nominal scoring[37].

Table 3.3 – Crowd-Rating Impacts on Financing: Sub-Indicators OLS Results

Components of the *z-Score*	*z-Success* **(1)**	*z-Usefulness* **(2)**	*z-Originality* **(3)**	*z-Ambitiousness* **(4)**	*z-Feasibility* **(5)**	*z-Affection* **(6)**	*z-CSR* **(7)**
Angel/VC at One Year	0.018*	0.005	-0.0006	0.009	0.015*	0.006	0.002
	(0.009)	(0.009)	(0.011)	(0.011)	(0.008)	(0.009)	(0.008)
Angel/VC at Two Years	0.006	0.002	-0.004	-0.001	-0.003	0.005	-0.001
	(0.006)	(0.008)	(0.011)	(0.010)	(0.007)	(0.006)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Indicators for Application Round	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the estimated coefficient β_1 from specification (10) for each component of aggregated score. The sample includes all projects that are evaluated from the crowd spanning 2015-2018. The first row focuses on the probability of financing events over the next year and the second row over the next two years. Outcomes are an indicator equal to one when ventures experienced funding round. All specifications control for application round fixed effects and observable characteristics. Standard errors are clustered at the project level.
** Significant at $p < 0.05$

In the first row (1), the point estimates suggest that the standardized score measuring the likelihood of success and appreciation of the feasibility of the project are positively associated with the likelihood of subsequent financing events over the next year conditional on observable characteristics, with the impacts statistically significant at conventional levels. For example, the point estimate in column (1) suggests that one standard deviation increase in success' score by a project in the evaluation process increases the probability of subsequent funding rounds over the next year by 1.8 percentage points. A one standard deviation increase in feasibility's score also predicts an increase in the probability of making a deal with early-stage investors by 1.5 percentage points over the next year. In contrast, point estimates in the second row for each component are statistically insignificant with the likelihood of funding rounds in the next two years.

I interpret these results as shedding light that there is heterogeneity in the crowd-rating components, particularly for both success and feasibility questions. On average, these components predict the venture's quality in the short-term. A potential explanation for the positive impact of these components on subsequent financing deals is that upvoters interpret them as the main determinants of success relative to the other questions.

[37] Note that my results are similar to the nominal score as the main independent variable.

5.3 *Robustness and Heterogeneity*

Robustness. In this section, I use several tests to provide evidence of the robustness of the main findings against two possible concerns with the estimated crowd-rating impact on subsequent financing events, including *(i)* potential identification issues or *(ii)* unobserved characteristics that are correlated with the crowd-rating. Robustness tests are in Appendix Tables 3.B.7 and 3.B.8.
As discussed in Section IV, my 2SLS estimates are interpreted as the causal impact of the crowd-rating under the assumption that my evaluator leniency instrument only affects venture outcomes through the aggregated score display on the platform, rather than through other channels. One concern is that evaluators can directly interact with ventures through feedback, and hence may affect how ventures respond as they learn about their quality, regardless of the aggregated score[38]. To address this concern, I estimate results that control for whether the venture received feedback, including a binary indicator. By controlling for whether evaluators post feedback, I can test whether my results are driven by the crowd-rating, or confound by another channel. In column (1) of Appendix Table 3.B.7, point estimates are similar to the baseline specification with no detectable impact of the crowd-rating on subsequent financing events over the next two years. These findings suggest that the exclusion restriction is unlikely to be violated by evaluators' feedback.

Another potential threat of the exclusion restriction is that the community of users attracts potential investors, which could directly invest in ventures reducing the search costs. I extend the analysis to consider whether evaluators would like to invest in a project. I can address this concern to some extent in 2SLS estimates by controlling for whether evaluators would be willing to invest. 2SLS estimates in column (2) show no statistically significant results in the crowd-rating impact on the probability of financing deals. This suggests that evaluator interest does not drive baseline results.

The remaining columns of Appendix Table 3.B.7 examine the sensitivity of my instrumental variable results to alternative specifications. In column (3), I instrument the standardized score using a residualized leave-out leniency measure by application round fixed effects, and in column (4) I use the leave-out mean instrument that pools projects across application rounds. Column (5) uses the same instrument as in baseline

[38]In a Bayesian framework, independent of the crowd-rating, feedback can increase the precision of the signal, as feedback (i.e., signal) increase. For example, Zimmermann (2020) finds that subjects receiving positive feedback after an IQ test performance adjusted their beliefs upwards, while negative feedback has an inverse effect on subjects.

specification but restricting evaluator sample that handled a minimum number of projects to reduce concerns about a potential noisy instrument (Bhuller et al., 2020). Column (6) shows point estimates corrected by bootstrap-clustered standard errors. Finally, columns (7-8) adds controls for venture technologies and additional observable venture characteristics[39]. In this setting, the assignment of evaluators is not random, selection could bias baseline results with a simple leave-out mean measure of evaluator leniency. The residualized leave-out evaluator leniency measure accounts for potential project selection. Using this instrumentation, my main results are statistically unaffected and the crowd-rating impact rises slightly. Finally, when I add controls for technology and additional venture characteristics at the time of application, results are similar to my baseline specification.

At last, Appendix Table 3.B.8 reports Anderson-Rubin (AR) confidence intervals at the 95 percent level. The AR test has statistical power against weak instruments in just-identified models. Hence, the probability to reject the null hypothesis when the null is violated is as well higher than the probability of rejecting the null when the null is correct (Andrews et al., 2019)[40]. Comparing the standard Wald confidence intervals with AR, differences are modest. Therefore, I can reject the null hypothesis of weak instruments.

How much selection on unobservables would be necessary to explain a moderate causal effect of the crowd-rating and subsequent financing events? The OLS results in Table 3.2 are sensitive to adding controls, the informativeness of the crowd-rating falls to 0.013, and a negative insignificant estimate in the 2SLS approach. One potential concern is that OLS estimates are biased by unobserved factors correlated with selection into the evaluation and subsequent financing decisions. I assess the potential bias from omitted variables by using modified approaches of Altonji et al. (2005)[41]. This method consists of using selection on observables to identify the bias from unobservable and the sensitivity of crowd-rating impact. Formally, a consistent estimator to assess the potential bias is derived from estimated coefficients and regression quality from uncontrolled and controlled estimates, without and with observable characteristics respectively. Thus, the consistent

[39] Column (8) of Appendix Table 3.B.7 adds controls for the number of words contained in the pitch, for the business models, B2B, B2C, and B2B2C), for whether ventures have at least one serial entrepreneur, one woman and a student in the founder team at the time of application.

[40] See Andrews et al. (2019) for a survey on detection of weak instruments, weak instruments robust inference, and his implications in empirical setting.

[41] In particular, I use the approaches developed by Bellows and Miguel (2009) and Oster (2019) to test the sensitivity of my estimates due to unobserved factors. For details on the consistent estimator of the coefficient of interest and underlying statistical assumptions, see Oster (2019).

estimator of the bias is defined as follows:

$$\beta^* = \beta^C - [\beta^U - \beta^C] \times \frac{R_{max} - R^C}{R^C - R^U} \tag{3.14}$$

where β^U and R^U are the estimated coefficient and the R^2 from the uncontrolled estimate, and β^C and R^C are the estimated coefficient and the R^2 from the controlled estimate. Finally, R_{max} denotes the R^2 from a regression of the outcome on observable and unobservable characteristics, that is unknown to the econometrician[42]. To evaluate the impacts of unobservables I use four statistical assumptions to bound R_{max}: *(i)* the Bellows and Miguel (2009) approach with R_{max}=(2R^C - R^U), *(ii)* the Oster (2019) approach with R_{max}=1.3R^C, *(iii)* an alternative approach from Oster (2019) with R_{max}=2.2R^C, and *(iv)* a conservative approach where R_{max} bounds as one. Appendix Table 3.B.9 and Appendix Figure 3.B.4 present intervals of estimated coefficients for crowd-rating impacts implied by statistical assumptions on R_{max} and δ to test the null hypothesis β_1=0. Columns (1-2) report point estimates from uncontrolled and controlled regressions. The remaining columns report the intervals. In three of my specifications (columns 3-5), the identified interval sets exclude a lower bound less than zero[43], providing evidence of a positive causal impact of the standardized score on subsequent financing events as of one year after the evaluation process. In contrast, under the statistical assumption of R_{max}=1, the identified set increases, including a lower bound smaller than zero. However, this assumption assumes no measurement error in the outcome, which seems implausible with real-outcomes (Gonzalez and Miguel, 2015). Finally, the related δ ratio range from 0.3 to 4.7 and 0.08 to 0.7 for the probability of financing measured at one and two years, respectively. For example, a δ ratio of 3 suggests that selection on unobservable would have three times greater than selection on observables to explain the entire crowd-rating impacts through the linear probability model.

Together, these results provide evidence that the crowd-rating impacts by OLS approach, even if it is statistically insignificant at conventional levels, are driven by selection on unobservable. However, selection on unobservable is roughly twice as small for my outcome measured at one year than two years.

Heterogeneity. The crowd-rating impacts on the probability of subsequent financing rounds as of one and two years after the evaluation process is small and insignificant.

[42]Note that the R_{max} is bounded under one due to classical measurement error in the outcome variable. Given this bounding, I can formulate several plausible values of R_{max} that reflect how much variation in the probability of funding rounds could be explained whether I had the full set of control variables (Gonzalez and Miguel, 2015).

[43]Note that increasing assumptions on the R_{max}, the identified intervals are wider, with a lower bound decreasing from 0.011 to -0.027.

Table 3.4 – Heterogeneity by Observable Characteristics

Dependent Variable	Impact at One Year			Impact at Two Years		
	Angel/VC	Survival	Has One Employee	Angel/VC	Survival	Has One Employee
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
By Venture Characteristics						
Incorporated	-0.003	0.001	0.020	-0.004	0.008	-0.002
	(0.045)	(0.061)	(0.117)	(0.049)	(0.130)	(0.148)
Not Incorporated	-0.072	-0.069	-0.010	0.010	-0.139	0.008
	(0.061)	(0.128)	(0.133)	(0.020)	(0.146)	(0.135)
Incubator/Accelerator	-0.043	0.027	-0.037	-0.044	-0.143	-0.235
	(0.095)	(0.096)	(0.179)	(0.084)	(0.157)	(0.210)
No Incubator/Accelerator	-0.042	0.039	-0.0009	0.012	-0.038	0.037
	(0.035)	(0.073)	(0.101)	(0.018)	(0.121)	(0.116)
VC Hub	-0.019	-0.043	0.016	0.058	-0.133	0.108
	(0.061)	(0.115)	(0.154)	(0.065)	(0.228)	(0.207)
No VC Hub	-0.039	-0.011	-0.020	-0.018	-0.063	-0.059
	(0.042)	(0.062)	(0.106)	(0.015)	(0.116)	(0.122)
Business Idea	-0.020	-0.259*	-0.105	-0.062	-0.327*	-0.059
	(0.051)	(0.137)	(0.154)	(0.044)	(0.170)	(0.144)
Launched Innovation	-0.036	0.129*	0.051	0.032	0.166	0.004
	(0.041)	(0.073)	(0.106)	(0.036)	(0.123)	(0.140)
By Team Characteristics						
Has at least one Female	-0.086	-0.037	0.103	0.001	-0.331	0.037
	(0.107)	(0.176)	(0.233)	(0.081)	(0.423)	(0.357)
All Male	-0.006	-0.008	-0.010	0.005	-0.034	-0.036
	(0.035)	(0.068)	(0.093)	(0.025)	(0.100)	(0.113)
Has Serial Entrepreneur	-0.058	-0.124	0.022	-0.076	-0.019	0.344*
	(0.070)	(0.099)	(0.155)	(0.080)	(0.239)	(0.202)
First Experience	-0.034	0.014	-0.037	0.026	-0.096	-0.178
	(0.038)	(0.079)	(0.101)	(0.026)	(0.116)	(0.126)

Notes: This table presents 2SLS estimates of the impact of crowd-rating by venture characteristics. The sample includes all projects that are evaluated from the crowd spanning 2015-2018. 2SLS specification instrument for crowd-rating using an evaluator leniency measure that is estimated using data from other evaluations evaluated by a platform's user in the same year. All specifications control for application round fixed effects and observable characteristics. Standard errors are clustered at the project level.
* Significant at $p < 0.10$

Although the impact could be heterogeneous conditional on baseline characteristics observed by evaluators. Columns (1-6) of Table 3.4 report several specifications estimate by 2SLS, dividing the analysis sample by both venture and founder characteristics[44]. In each heterogeneity analysis, I estimate specification (13) in which all coefficients are allowed to vary by subsample. A conventional test of the null hypothesis that the effect of the crowd-rating is the same across subgroups is conducted.

[44]The heterogeneity results across venture and founder characteristics are not reported in Table 3.4 for the web traffic due to data limitation causing fairly imprecise estimates.

Rows (1-8) of Table 3.4 report 2SLS subsample results by venture characteristics: incorporated versus non-incorporated ventures, whether ventures participated or not an incubator or accelerator programs, whether ventures are located or not in a VC hub, and according to the development stage. I find that the impacts of the crowd-rating are similar across all these characteristics and imprecisely estimated. These results support a conclusion of no heterogeneity effect across venture characteristics. However, the largest estimates are for ventures that are not incorporated at the time of application (-0.072, s.e.=0.061). Unlike in Howell (2019) that evaluate judges predictive power in new venture competitions, these findings support the idea that the crowd may identify high growth potential for less mature and uncertain ventures and be more strict for other ventures. Rows (9-12) consider different founder characteristics. Both at one and two years, I do not find heterogeneity treatment effects for prior entrepreneurial experience. This result does not support the idea that is easier to screen project with team members which have prior entrepreneurial experience (Ewens and Townsend, 2020; Howell and Nanda, 2019). Similarly, I find that the impact on ventures with at least one woman is the largest on the probability of early-stage financing over the next year and an inverse relationship over the next two years, although point estimates are not different from zero and less precisely estimated.

A potential explanation for no evidence of heterogeneity effects is the possibility that evaluators set similar scores based on observable characteristics. Appendix Figure 3.B.5 compares the distribution of the nominal score for heterogeneity subsamples and shows that score distribution among the observable characteristics are highly similar, but I observe a small right shift for ventures that participate in incubator or accelerator program and that for some subsamples the distribution is left-skewed. These visual and heterogeneity analyses are not consistent with the possibility that the evaluators discriminate and place a cut-off rule (i.e., higher or lower threshold) for scoring projects based on the characteristics of the project.

5.4 *Impacts of Crowd-rating on Venture Outcomes*

So far, I have focused on how the crowd-rating impacts subsequent financing events and whether it can reveal information to potential early-stage investors. But the crowd can reduce information frictions by predicting real venture outcomes success. In this section, I examine the crowd-rating impacts on venture markers of success using the evaluator IV strategy for three measures: venture survival, have at least one employee, and the web traffic (see Section II for variable descriptions).

I begin the analysis of the crowd-rating impact on venture outcomes with visual evidence. Appendix Figure 3.B.3 plots residualized venture outcomes against the standardized score. There is an upward-sloping relationship between venture survival (Panel A), the indicator for having at least one employee (Panel C) over the next year, and the standardized score, suggesting predictive power of evaluations from the crowd on short-term real outcomes. In contrast, remaining panels do not provide visual evidence of a positive relationship between the standardized score and real outcomes measured at two years. In particular, for the web flow as of one and two years after the evaluation process, the slope is near to zero in different parts of the sample distribution of the score, suggesting a null crowd-rating impact.

In Table 3.5, I present a series of OLS and 2SLS estimates of crowd-rating impacts on venture outcomes. I baseline specification in columns (1-3-5) controls (2-4-6) only for the application round fixed effects, and other columns control for observable characteristics and the log number of upvoters. Panel A and C present OLS estimates for the short-run and medium-run impacts, respectively. Point estimate in column (1) suggests that projects with higher crowd-rating are more likely to survive in the short-run. When I add controls, the estimated crowd-rating impact decreases to 0.067 (s.e.=0.017) but remains significant at the one percent level. In the short-run, a one standard deviation increase in the score experienced by a project at the time of evaluation process thus increases the likelihood of venture survival over the next year by 6.8 percentage points[45]. Over the next two years, the crowd-rating impacts are also positive on survival, but not statistically different from zero. This result is consistent with visual evidence in Appendix Figure 3.B.3 and with the short-run positive impact of both success and feasibility score reported in Table 3.3. Point estimates in columns (3-4) show that the crowd-rating has a positive correlation with employment with and with controls for project attractiveness and observable characteristics. The point estimate in column (4) implies that a one standard deviation increase in the standardized score is associated with a 5.1 percentage point increase in the likelihood of having at least one employee. In contrast, the estimated impact is not statistically significant over the next two years once I add controls. Finally, in the remaining columns, I examine whether on average the crowd-rating improves the venture's web traffic. The estimated coefficient is positive and statistically significant over the next two years. Controlling for the number of upvoters and observable characteristics in column (6) reduce the standardized score by 0.49 and 0.29 log points in the short and medium-run, respectively. This result

[45]Overall, 14.2 (66 projects) percent of projects or ventures do not survive as of one year after the evaluation process, and 24.5 (79 projects) percent over the next two years.

suggests that evaluators have predictive power for venture measures of success as of one and two years after the evaluation process. One interesting is whether a higher score is associated with long-run web traffic for larger observations than in my specification and whether web performance is related to prior financing deals (Kerr et al., 2014).

Table 3.5 – Crowd-Rating Impacts on Startup Outcomes: OLS and 2SLS Results

Dependent Variable	Survival		Has One Employee		log(#Web Flow)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Impact at One Year: OLS						
z-Score	0.081***	0.067***	0.068**	0.051*	1.023***	0.533**
	(0.021)	(0.017)	(0.027)	(0.026)	(0.309)	(0.270)
Obs.	467	461	453	447	206	203
R^2	0.04	0.17	0.06	0.16	0.07	0.37
Mean Dependent Variable	0.858	0.861	0.485	0.487	4.441	4.507
Panel B. Impact at One Year: 2SLS						
z-Score	0.003	-0.024	0.029	-0.004	0.664	-0.202
	(0.065)	(0.064)	(0.097)	(0.089)	(1.014)	(1.008)
Obs.	442	436	428	422	190	187
R^2	0.02	0.12	0.05	0.13	0.07	0.33
Mean Dependent Variable	0.861	0.864	0.485	0.487	4.525	4.595
Panel C. Impact at Two Years: OLS						
z-Score	0.044	0.038	0.071**	0.053	1.148***	0.855**
	(0.031)	(0.029)	(0.034)	(0.035)	(0.402)	(0.368)
Obs.	323	317	312	306	180	177
R^2	0.02	0.14	0.04	0.15	0.17	0.38
Mean Dependent Variable	0.755	0.760	0.445	0.447	4.027	4.096
Panel D. Impact at Two Years: 2SLS						
z-Score	-0.051	-0.084	0.017	-0.023	0.960	0.655
	(0.114)	(0.105)	(0.118)	(0.107)	(0.976)	(0.940)
Obs.	318	312	307	301	177	174
R^2	0.01	0.09	0.03	0.14	0.18	0.38
Mean Dependent Variable	0.751	0.756	0.446	0.448	3.955	4.023
Controls	No	Yes	No	Yes	No	Yes
Indicators for Application Round	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the estimated coefficient β_1 from OLS and 2SLS of the impact of crowd-rating. The sample includes all projects that are evaluated from the crowd spanning 2015-2018. 2SLS specification instrument for crowd-rating using an evaluator leniency measure that is estimated using data from other evaluations evaluated by a platform's user in the same year. Columns (1-2) show the estimated crowd-rating impact on venture survival over the next year (Panel A) and two years (Panel B), columns (3-4) focus on an indicator for whether the venture has at least one employee, and columns (5-6) focus on the yearly average web traffic. All specifications control for application round fixed effects and observable characteristics. Standard errors are clustered at the project level.
* Significant at $p < 0.10$
** Significant at $p < 0.05$
*** Significant at $p < 0.01$

The 2SLS estimates in Panels B and D show that the point estimates are smaller in magnitude and less precisely estimated than OLS estimates. These 2SLS estimates suggest crowd-rating has no causal impact on venture real outcomes. For example, adding control variables, point estimates on venture survival range from -0.024 to -0.084 as of one and two years after the evaluation process with standard errors around 0.064 and 0.105. 2SLS estimates on whether ventures have at least one employee and web traffic in the short-run, likewise show no statistically significant evidence of impact but are too imprecise to rule out no impact even very small and draw firm conclusion[46]. Taking together, these results highlight that evaluation relying on the crowd to score projects has no screening power and is unsuccessful to identify venture success as measured by real outcomes in the short and medium-run. My results contrast with the ability of expert judge panel in assessing venture ideas (Howell, 2019; McKenzie, 2017). However, projects with higher scores and those receiving feedbacks from evaluators can encourage the founding team to pursue, through a signaling mechanism (Åstebro and Elhedhli, 2006; Howell, 2018).

Robustness. In Appendix Tables 3.B.7 and 3.B.8, I consider the robustness of the crowd-rating impacts on real venture outcomes, along the same specifications, examined for my subsequent financing events measures. Across all alternative specifications, my 2SLS estimates are nearly similar to my baseline specification and find the score from the crowd positively does not improve venture outcomes as of one and two years after the evaluation process, although my estimates turn not statistically different from zero. In particular, using the leave-out mean instrument constructed on a subsample of evaluators affects my point estimates on survival and the web traffic over the next two years, yielding a positive impact but indistinguishable to zero. Finally, using the AR test the confidence intervals suggest that the instrument is not weak.

Heterogeneity. In Table 3.4, I present heterogeneity of the crowd-rating impacts on real venture outcomes, along the same specification consider for subsequent financing events. Similar to subsequent financing results, I find no evidence of heterogeneity impact on venture real outcomes across observable characteristics, but small significant effect of crowd-rating on whether ventures have at least one employee. A one standard deviation increases in the crowd-rating experience by venture increases the probability of having at least one employee in the team by 34.4 percentage points, rejecting the null hypothesis of equal effects *p-value* of 0.02. Finally, I consider subsamples based on the development

[46] Point estimates are near to zero with a 95% confidence interval that ranges from -0.17 to 0.17 for employment outcome and -2.17 to 1.77 for web traffic.

stage. The likelihood of survival is larger for projects that have launched an innovative product or service (0.129, s.e.=0.073) than for projects at the business idea level (with a negative effect of the crowd-rating, -0.259, s.e.=0.137). This pattern is supportive of the idea that team members learn from the score.

5.5 *External Validity: Comparison of 2SLS with OLS*

The results show that OLS estimates are larger than the 2SLS estimates. A limitation to 2SLS results is that it provides LATE for a subset of ventures for whom evaluation from the crowd is affected by the set of evaluators and their leniency, and cannot be generalized to average ventures (Doyle Jr et al., 2015). This caveat has been stressed in the literature in other settings that use similar instrumentation identification based on quasi-random assignments of examiners or judges[47]. For example, ventures with low project quality will receive a lower scoring even by a lenient evaluator while a high-quality project will receive higher scoring even from a strict evaluator. Therefore, I am unable to identify the effects of ventures with low (i.e., never takers) and high quality (i.e., always takers), but only for the subset ventures that I expect to be responsive to the exogenous variation of evaluator leniency measure (i.e., compliers). Even though OLS estimates the average treatment effect (ATE) plus the selection bias, point estimates through OLS could be upward-biased if the selection bias is positive[48]. Thus, my 2SLS estimates are smaller than OLS if the difference between the estimated LATE and ATE is smaller than the selection bias. But since the impact on ventures suggests a causal impact which is close to zero, the impact is likely due to selection. Relatedly, interpreting the estimated effect as LATE involves a monotonicity assumption. Reassuringly, the monotonicity assumption is likely to hold in my settings.

6 Conclusion

Technological shocks had important implications for starting a new business, falling the cost of entry and experimentation. These changes have caused a shift in the investment strategy of early-stage investors, increasing a new range of opportunities. However, higher information asymmetries and uncertainty about the quality of business ideas have increased difficulty to identify high-return ventures for potential early-stage investors.

[47] See for example Dahl et al. (2014) that examine the causal effects of family welfare cultures in Norway's disability insurance system or Dobbie et al. (2018) or Bhuller et al. (2020) that estimate the causal effects of pre-trial detention on subsequent defendant outcomes.

[48] For example, ventures that launch on the platform a project with higher unobserved quality are more likely to have high-growth potential, to attract early-stage investors and to survive, regardless of the crowd-rating while ventures with low potential are more likely to abandon.

The emergence in recent years of new intermediaries that screen and select ventures at the earliest stage of their lifecycles such as accelerators, business plan competition, and investment readiness programs has support experimentation. New intermediaries could produce an informative signal to early-stage investors, reducing information frictions. Quasi-experimental studies find strong impacts of judge experts to assess the quality of ideas and subsequently attract external financing (Howell, 2019; Gonzalez-Uribe and Reyes, 2019). Despite the growing use of new intermediaries, evaluations from the crowd are scarce (Cao, 2020). This chapter contributes to this literature by providing statistically precise enough estimates of the causal impact of the crowd-rating on real venture outcomes, using plausibly exogenous variation in the score leniency to address concerns about correlated unobservable characteristics. For subsequent financing events and venture success, the results report estimates that are not statistically significant both in the short and medium-run, but often precise enough to rule out even small impacts of the crowd-rating. There are possible exceptions to the indistinguishable to zero impacts are that subcomponent of the overall score appears to be positively related to the probability of financing in the short-run.

Nevertheless, in the 10 subsamples considered in the heterogeneity analysis, there is one important deviation from the baseline estimates. The crowd-rating appears to be informative and produce valuable signals for the founder team once I take into account underlying riskiness in project quality, as revealed by the development stage. A one standard deviation decrease in the score experienced by venture at the idea stage thus decreases the probability of survival over the next year by 25.9 percentage point, while ventures at a later stage that proposed a final product or service are more likely to survive. These estimates are precisely estimated. Since ventures with pre-product reduce uncertainty about the project quality, I interpret this finding as suggestive evidence that it is easier for the crowd to discriminate project based on proof of concept, and those founders update beliefs on whether continue or abandon their project.

The results suggest that in the context of project evaluation using an online community, the impact on venture outcomes is null. With the exception of venture survival in the short-run in one subsample, my results are not distinguishable to zero, in contrast to the small literature on the crowd as new intermediaries. For example, Cao (2020) documents large positive effects of the crowd-ranking on funding raised from VC over the next year. However, the analysis sample is restricted to ventures that launched a realized product and do not control for observable venture characteristics that could be related to quality. More broadly, my conclusions are consistent with the findings from experimental studies (McKenzie and Sansone, 2019; Cusolito et al., 2020) of expert's judges scoring entrepreneurial ideas in developing countries, which document the difficulty to predict subsequent success.

These results are directly relevant for digital platforms using reviewers and investors attempting to predict which early-stage ventures has high growth return in countries other than the U.S. While relying on the crowd is less costly and time-consuming than other new intermediaries and could signal early-stage venture success, the impacts will appear uncorrelated with real outcomes in the next years after the evaluation process. This highlights the growing uncertainty and riskiness of venture at a very early-stage life cycle and the difficulty for potential investors to manage the funnel to find promising high growth returns. Thus collective intelligence is unlikely to be an effective screening process for reducing information frictions and improving investor decision-making strategies.

There are three caveats to my analysis. First, even if this chapter provides causal estimates of the impact of the crowd-rating on a wide set of venture outcomes, the analysis sample is small. The sample size is restricted by external constraints that unable to estimates the impact of project evaluation from the crowd on a larger sample. This constraint could result in a lack of statistical power to reject the null hypothesis. However, point estimates are close to zero, and precisely enough estimated and confidence intervals allow to rule out that the evaluation has large impacts on venture success measures. Second, related to this concern, the results are condition on ventures or entrepreneurs that launched a project on the online platform and that is evaluated by the community of users. The selection that occurs can attract project with heterogeneous quality and subsequent success, in particular ventures at a very early stage of their cycle or founders with higher uncertainty. For example, it may be easier to evaluate projects with low-quality threshold and high growth potential ventures will succeed anyway, resulting in zero average effect. Finally, it is important to emphasize the local nature of the estimates around the quasi-random assignment of evaluators. However, my local estimates have important implications for early-stage investors as well as founders themselves. Assessment of business ideas from external investors is concentrated with few deal opportunities to end with a very small number of investments (Gompers et al., 2020). Evidence from other populations would be useful to assess the effectiveness of the crowd to signal venture quality.

Appendix

3.A Scoring Methodology, Variable Definitions, and Additional Summary Statistics

3.A.1. Scoring Methodology

Scoring. Applications launched on the online platform were scored by the crowd, which consists of a community of users. This community encompasses potential investors, experts, coaches, mentors, and users interest in new technologies. Each application is evaluated on the basis of seven different questions as follows:

- *Success*: In your opinion, is this offer likely to succeed?
- *Usefulness*: Does this project seem useful to you?
- *Originality*: Does the project seem original to you?
- *Ambitiousness*: Does the project seem ambitious to you?
- *Feasibility*: Does the project have the means to meet its ambitions?
- *Affection*: Do you like this project?
- *CSR*: Does the project have an ecological or societal dimension?

Each of the seven questions was scored on a scale spanning 0 to 10. The nominal score from the crowd is a simple average of the seven scores of each evaluator (i.e., the crowd) that score project, ranging from 0 to 10. Then the following variable was calculated:

z-Score: Standardized z-scores of each of the above seven variables are obtained by subtracting their mean and dividing by their standard deviation. The standardized score is then the mean of the standardized z-scores for success, usefulness, originality, ambitiousness, feasibility, affection, and CSR criteria. Appendix Figure 3.A.1 plots the nominal score against the standardized score (i.e., z-Score), showing a high correlation between the two variables.

3.A.2. Variable Definitions

Angel Investment: angel investment is a binary indicator that takes value one if the venture or project received external financing round from angels investors spanning 2015 to 2019, and zero otherwise. The variable is coded for the next year and the next two years from the application year.

Venture Investment: venture investment is a binary indicator that takes value one if the venture or project received external financing round from venture capitalist investors spanning 2015 to 2019, and zero otherwise. The variable is coded for the next year and the next two years from the application year.

Venture Survival: venture survival is a binary indicator coded as one if the venture is still operating over the next year and the next two years after the evaluation process, and 0 otherwise.

Has One Employee: employment measure is a binary indicator coded as one if the venture has at least one employee in addition to the founder team over the next year and the next two years after the evaluation process, and 0 otherwise. The variable is coded as zero if the venture or project is closed.

#Web Flow: web flow is the yearly average of web visits that the venture's website received in a given year. The variable is coded as zero if the venture does not have an active website or is closed. The variable is winsorized at the 95 percent level to reduce the influence of outliers.

Venture Age: venture age is defined as the number of years since the venture is incorporated and coded as zero if the venture is at the project stage (i.e., idea).

Incorporated: incorporation status is a binary indicator coded as one if the venture is incorporated in the official registry of commerce, and zero otherwise. The variable is coded as zero if the venture is closed in a given year.

Incubator/Accelerator: incubator/accelerator is a binary indicator coded as one if the venture has participated in an incubator or accelerator program prior to the application on the online platform, and zero otherwise.

Has a website: has a website is a binary indicator coded as one if the venture has an active website at the time of the application on the online platform, and zero otherwise.

#Word Pitch: word pitch is the number of words in the pitch deposit on the online platform and coded as zero if the pitch is empty.

VC Hub: VC hub is a binary indicator coded as one if the venture is located in a VC hub defined as a dominant hub of entrepreneurial activity in France, and zero otherwise.

Business Model: the business model is a binary indicator split by customer segments with B2B, B2C, and B2B/B2C. The variable is coded as one for the three different business model, and zero otherwise.

#Founders: the number of founders is defined as the number of physical persons that claim to be part of the founding team on official documents deposed on the platform. This measure is completed with information on active or inactive Linkedin profiles of persons that claimed to be part of the founding team at the application time.

Founders Age: for each founder identified, the founder age is defined based on birth year available in the official registry of commerce or is approximated as the high school graduation year less 18.

Serial Entrepreneur: is a binary indicator coded as one if a member of the founding team was previously the Chief Executive Officer (CEO) or founder of a different venture, and zero otherwise.

#Jobs: the number of jobs is defined as the number of employment since the venture or project was launched on the online platform.

Student: the student status is a binary indicator coded as one if a founder was still in a training at the time of application.

Founder Graduation: founder graduation is a binary indicator (define separately for each degree) coded as one if a founder has an MBA/Master, or a Ph.D. or an engineering degree, and zero otherwise.

3.A.3. Additional Summary Statistics

Table 3.A.1 – Venture Distribution Across Technological Sectors

Sector	N	Fraction (%)
Art/Entertainment/Gaming	62	12.40
Beauty/Lifestyle	27	5.40
Clean Technology	43	8.60
Communication/Marketing	18	3.60
Education	18	3.60
Electronic	21	4.20
Energy	7	1.40
Event	11	2.20
Fashion	49	9.80
Financial Technology	18	3.60
Food	36	7.20
Hardware/Software/IoT	144	28.80
Healthcare	24	4.80
Legal/RH	18	3.60
Real Estate	16	3.20
Transportation	12	2.40
Travel	23	4.60
Social	15	3.00
Other	28	3.00

Note: This table presents the distribution of ventures (or projects) by technological sectors. Each venture is assigned to its main sector. N=500.

Table 3.A.2 – Financing Events Across Stage: Angel and Venture Capitalist

Stage	Angel	Angel (Levels)	VC	VC (Levels)
2015	0.008	2,500	0.002	700
2016	0.018	4,288	0.016	15,290
2017	0.012	4,280	0.036	29,860
2018	0.01	4,824	0.022	20,300
2019	0.01	3,100	0.026	49,900

Note: This table presents the distribution of ventures financing events by sources and by year.

Table 3.A.3 – Data Representativeness

	2015		2016		2017		2018	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Sector								
Art/Entertainment/Gaming	4	29	18	59	22	53	18	37
Beauty/Lifestyle	6	46	5	69	5	79	11	42
Clean Technology	1	13	6	19	6	17	30	19
Communication/Marketing	3	159	6	184	3	140	6	111
Education	0	19	8	26	2	24	8	22
Electronic	1	32	2	32	11	31	7	44
Energy	2	15	0	23	1	25	4	28
Event	0	10	0	20	4	18	7	14
Fashion	4	19	8	30	23	21	14	12
Financial Technology	2	42	3	76	9	77	4	66
Food	3	37	15	62	12	67	6	54
Hardware/Software/IoT								
Healthcare	1	62	6	85	8	133	9	86
Legal/RH	0	24	6	29	6	33	6	46
Real Estate	1	21	10	34	3	42	2	33
Transportation	1	54	4	83	5	70	2	47
Travel	1	26	4	60	7	39	11	27
Social	0	50	1	76	0	45	14	34

Note: This table presents the analysis sample representativeness. The table compares the distribution of ventures by technological sectors with the number of financing events by technological sectors reported in the French startup ecosystem (Dealroom).

3.A.3. Additional Figures

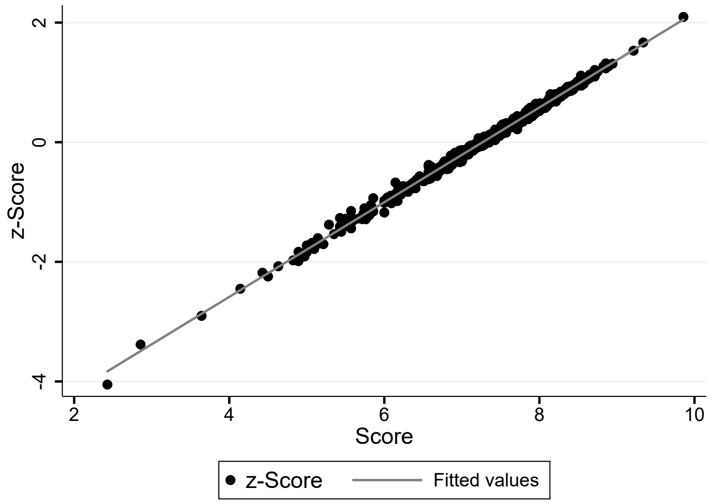
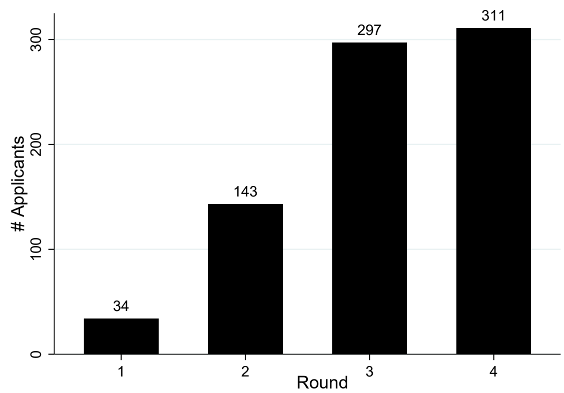
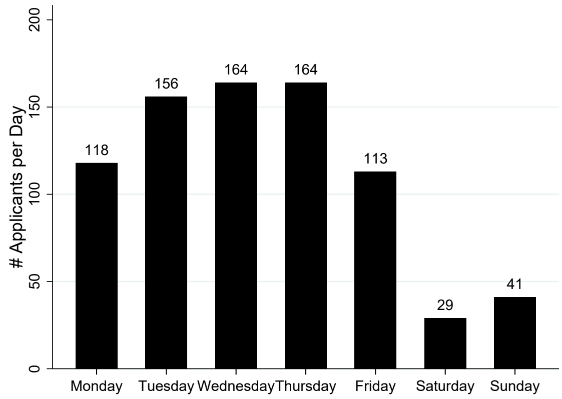


Figure 3.A.1 – Standardized and Nominal Score.

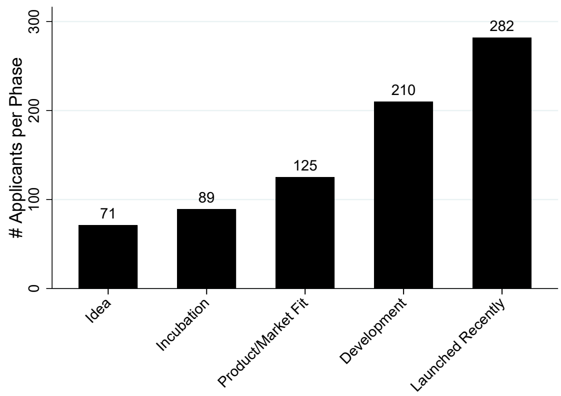
Notes: This figure plots the standardized score against the nominal score. Each dot represents a venture or entrepreneur that launched a project on the online platform. The correlation between the standardized score and the nominal score is 0.99



(a) *Application Round*



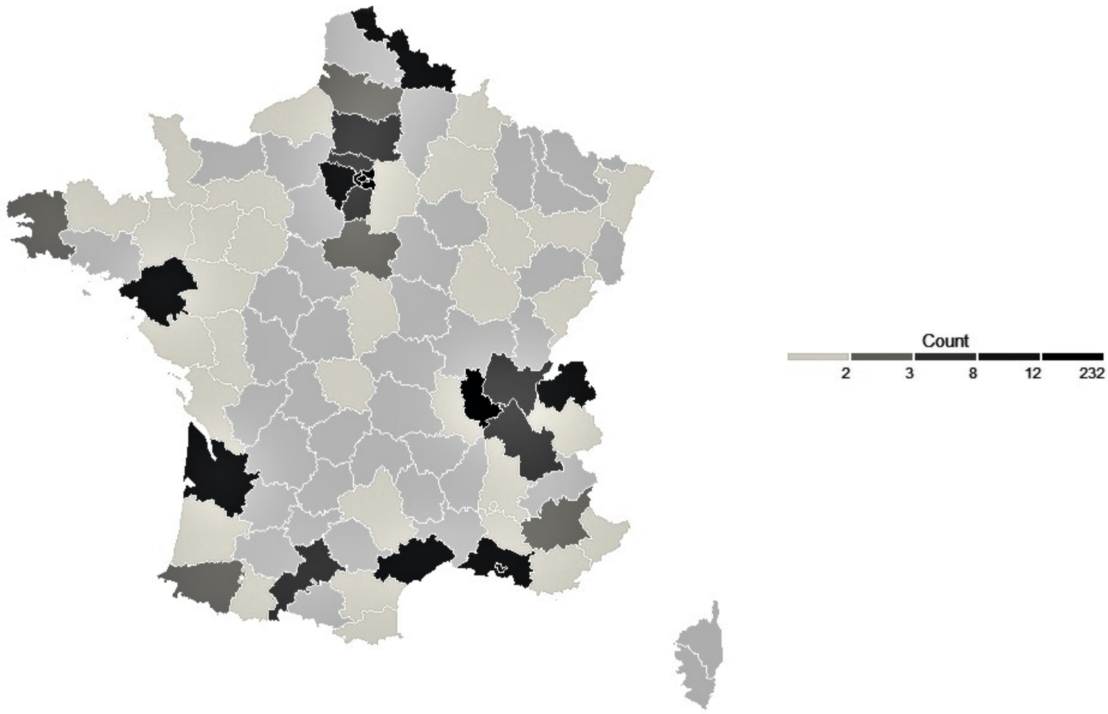
(b) *Day Application*



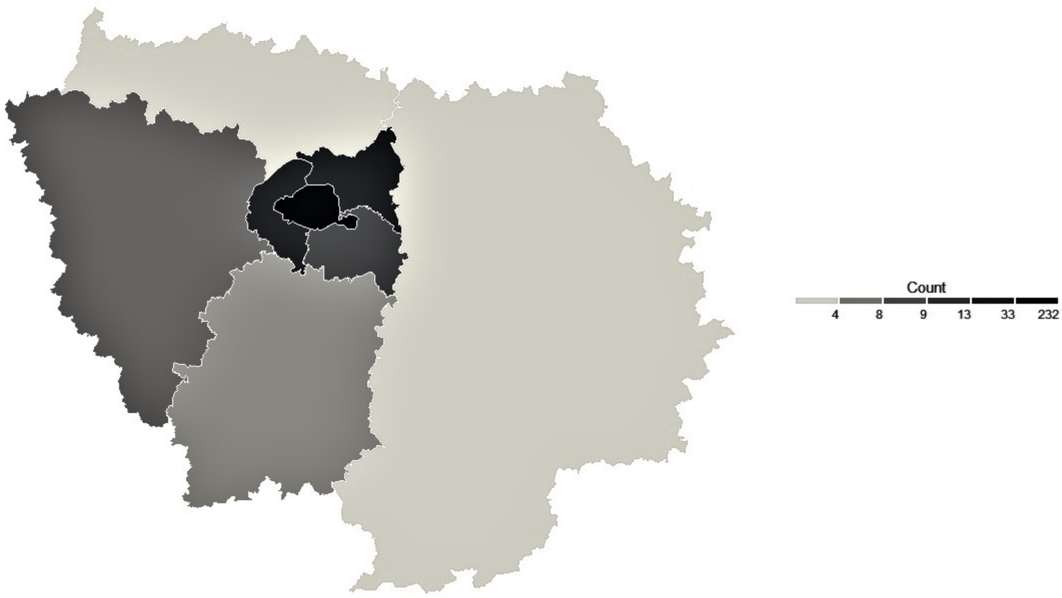
(c) *Phase Application*

Figure 3.A.2 – Time Trends of Project Applications.

Notes: This figure plots time trends in the number of projects launched on the online platform. Panel A shows project applications by rounds (years). Panel B shows the number of projects launched by day of the week and Panel C shows the number of projects launched by the development stage.



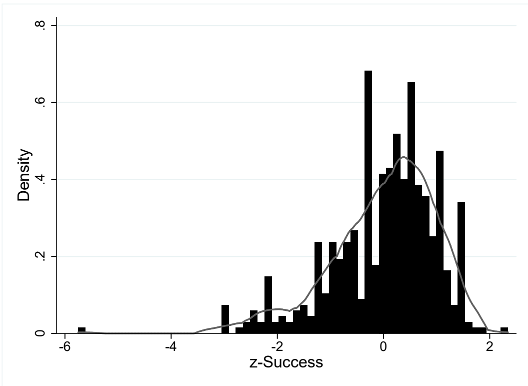
(a)



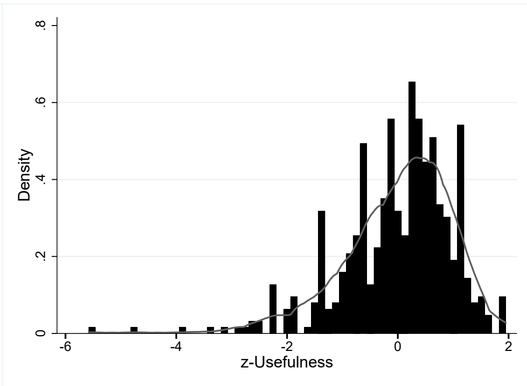
(b)

Figure 3.A.3 – The Geography of Project Application in France.

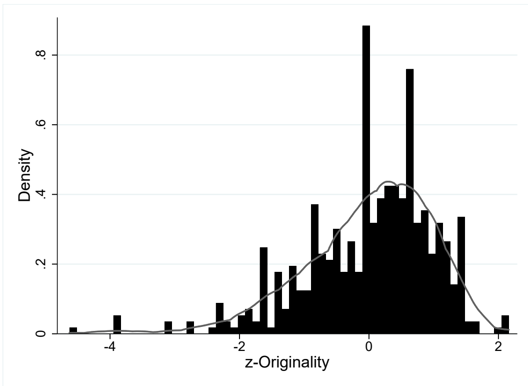
Notes: This figure presents maps of the count of ventures by french departments. Panel A shows the overall distribution by french areas while Panel B maps the Ile-de-France area (i.e., Paris Metropolitan Area).



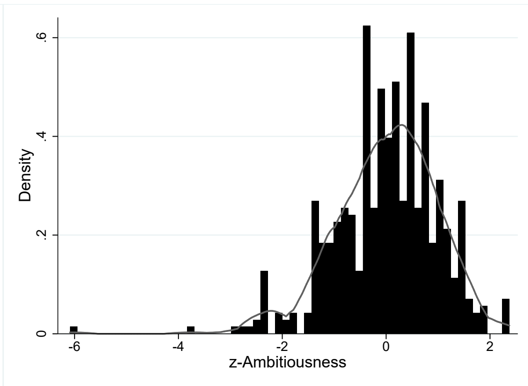
(a) *z-Success*



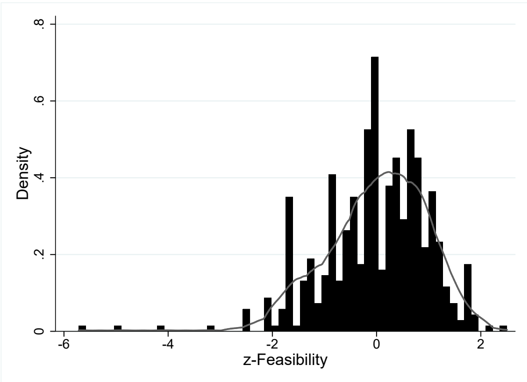
(b) *z-Usefulness*



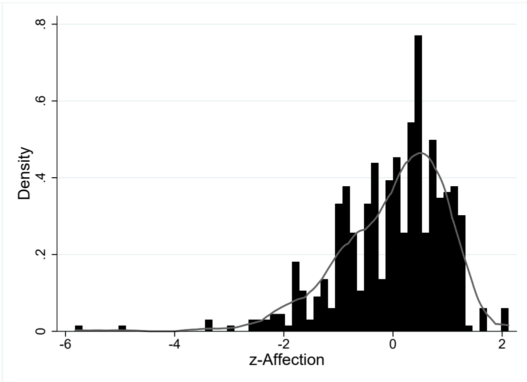
(c) *z-Originality*



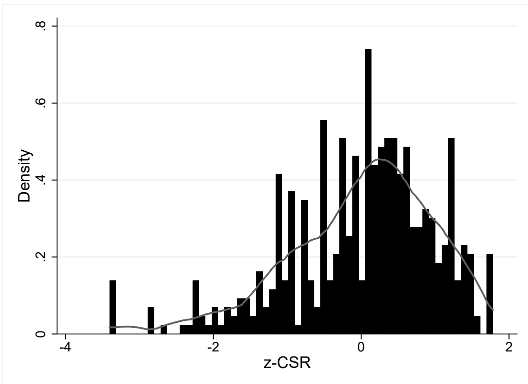
(d) *z-Ambitious*



(e) *z-Feasibility*



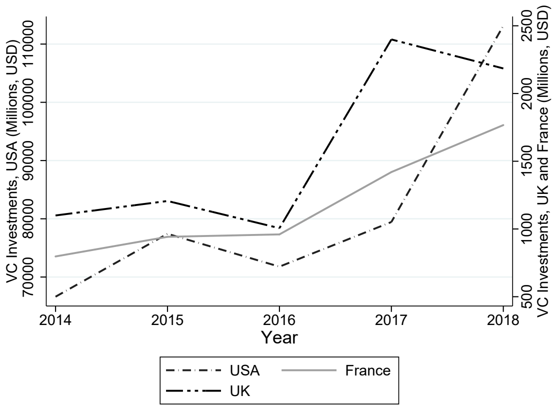
(f) *z-Affection*



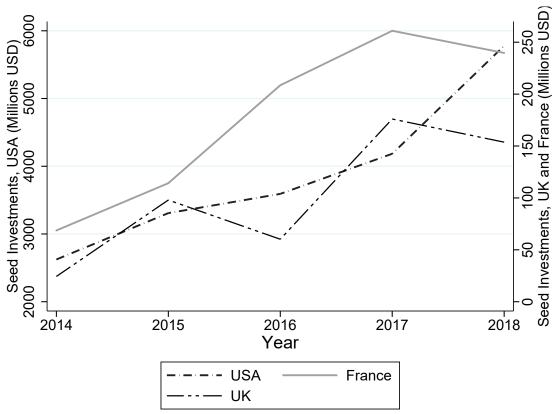
(g) *z-CSR*

Figure 3.A.3 – Distribution of the Standardized Score by Subcomponents.

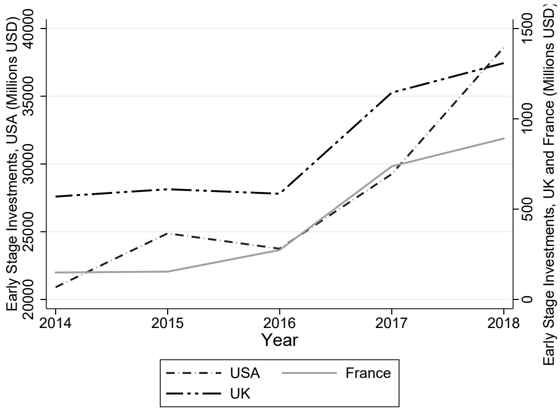
Note: This figure presents the standardized score for subcomponent scores from the crowd.



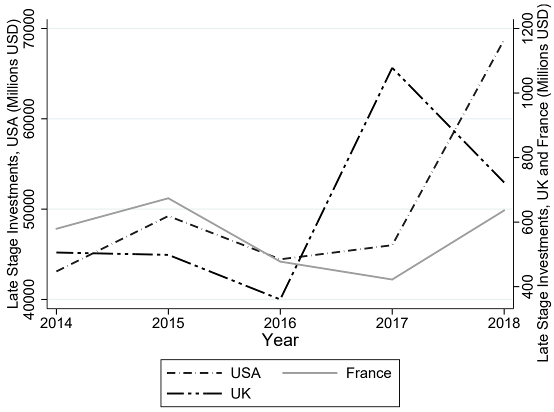
(a)



(b)



(c)



(d)

Figure 3.A.4 – Venture Capitalist Investment Trends in the U.S, the United Kingdom, and France.

Notes: This figure presents the venture capitalist investment trends in the U.S, the United Kingdom, and France by investment stages. Panel A shows total investments by venture capitalists. Panel B shows investment at the seed stage, Panel C at the early-stage, and Panel D at the late stage.
Source: OECD.

3.B Additional Results on the Crowd-Rating Impact

3.B.1. Identifying Assumptions

Table 3.B.1 – Impact of Observable Characteristics on Crowd-Rating and Success

Dependent Variable	*z-Score* (1)	Evaluator Leniency (2)	Angel/VC at One Year (3)	Angel/VC at Two Years (4)
Age	-0.002***	-0.0005	0.003***	-0.0008
	(0.001)	(0.0004)	(0.0006)	(0.0004)
Incorporated	-0.001	-0.004	0.019	0.013
	(0.074)	(0.035)	(0.024)	(0.016)
Incubator/Accelerator	0.030	-0.0009	0.067**	0.028
	(0.070)	(0.030)	(0.026)	(0.022)
Has a Website	0.114	0.075	0.038*	-0.001
	(0.111)	(0.047)	(0.020)	(0.020)
VC Hub	-0.153*	0.005	-0.003	0.040
	(0.084)	(0.038)	(0.034)	(0.034)
Prior Financing Round	0.184**	0.033	0.012	0.112**
	(0.097)	(0.036)	(0.037)	(0.045)
#Founders	-0.049	-0.040**	0.007	0.003
	(0.051)	(0.017)	(0.012)	(0.012)
log(#Upvoters)	0.285***	-0.019	-0.001	0.0001
	(0.045)	(0.020)	(0.008)	(0.006)
Obs.	461	436	461	317
R^2	0.09	0.09	0.13	0.14
Joint F-test	0.000	0.241	-	-

Notes: This table presents estimates for the venture characteristics on the standardized score (column 1), evaluator leniency (column 2) and ventures financing (columns 3-4) using the following specification: $Y_i = \beta_0 + \beta_1 X_i + \gamma_t + \varepsilon_i$, where X_i is a set of time-invariant observable characteristics. The model is OLS in columns (1-2) and a linear probability model in columns (2-3). All specifications include application round fixed effects. The *p-value* reported in the last row of columns (1-2) is for the F-test of joint significance of the observable venture characteristics. Standard errors are clustered at the project level.

Table 3.B.2 – Evaluator Leniency: First-Stage

Dependent Variable	*z-Score*		
	(1)	**(2)**	**(3)**
Evaluator Leniency	0.792***	0.850***	0.867***
	(0.109)	(0.117)	(0.117)
Obs.	474	436	436
F-statistics	52.44	52.65	54.16
Controls	No	Yes	Yes
Additional Controls	No	No	Yes
Indicators for Application Round	Yes	Yes	Yes

Notes: This table presents first stage estimates. Evaluator leniency measure is estimated using data from other evaluations evaluated by a platform's user in the same year. Column (1) reports estimate controlling for application round fixed effects. Column (2) adds observable venture characteristics: venture age, incorporation status, incubator or accelerator participation, whether ventures have a website, whether ventures are located in a VC hub, whether ventures have prior funding, the number of founders, and the number of upvoters. Column (3) adds additional control variables: whether ventures have at least one woman, a student, a serial entrepreneur, and indicators for the business model. All specifications control for application round fixed effects and observable characteristics. Standard errors are clustered at the project level. *** Significant at $p < 0.01$

Table 3.B.3 – Balancing Test: Observable Venture Characteristics

	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile	*p-value*
Age	1.80	3.07	1.49	1.62	0.47
Incorporated	0.53	0.48	0.53	0.49	0.50
Incubator/Accelerator	0.35	0.44	0.34	0.39	0.63
Has a Website	0.77	0.78	0.92	0.81	0.39
VC Hub	0.32	0.44	0.46	0.40	0.09*
Prior Financing Round	0.18	0.16	0.14	0.20	0.70
#Founders	1.53	1.56	1.57	1.47	0.61
log(#Upvoters)	1.98	2.35	2.23	1.76	0.09*

Notes: This table presents a balancing test of observable venture characteristics across quartiles of the distribution of the evaluator leniency measure. The last column reports a significance test for the difference in the group mean between the first and fourth quartiles.

Table 3.B.4 – First-Stage by Observable Characteristics

	z-Score									
Dependent Variable	Incorporated	Not Incorporated	Incubator Accelerator	No Incubator Accelerator	VC Hub	Not VC Hub	Prior Financing	No Prior Financing	Has Website	Hasn't Website
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Evaluator Leniency	0.844***	0.865***	0.687***	0.946***	0.798***	0.903***	0.574**	0.885***	0.885***	0.770***
	(0.158)	(0.169)	(0.172)	(0.145)	(0.197)	(0.144)	(0.265)	(0.129)	(0.128)	(0.265)
Obs.	239	197	171	265	185	251	74	364	363	73
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Indicators for Application Round	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents first stage estimates for subsample across venture characteristics. Evaluator leniency measure is estimated using data from other evaluations evaluated by a platform's user in the same year. All specifications control for application round fixed effects and observable characteristics. Standard errors are clustered at the project level.
** Significant at $p < 0.05$ *** Significant at $p < 0.01$

Table 3.B.5 – First-Stage by Additional Characteristics

Dependent Variable	*z-Score*							
	Business Idea **(1)**	Launched Innovation **(2)**	Has at Least One Female **(3)**	All Male **(4)**	Has Serial Entrepreneur **(5)**	First Experience **(6)**	Has at Least Student **(7)**	No Student **(8)**
Evaluator Leniency	0.811***	0.909***	0.672***	0.941***	0.791***	0.917***	0.761**	0.868***
	(0.180)	(0.120)	(0.210)	(0.142)	(0.185)	(0.155)	(0.357)	(0.124)
Obs.	166	270	160	276	148	288	55	381
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Indicators for Application Round	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents first stage estimates for subsample across additional venture characteristics. Evaluator leniency measure is estimated using data from other evaluations evaluated by a platform's user in the same year. All specifications control for application round fixed effects and observable characteristics. Standard errors are clustered at the project level.
** Significant at $p < 0.05$ *** Significant at $p < 0.01$

3.B.2. Additional Results and Robustness Tests

Table 3.B.6 – Crowd-Rating Impacts: Reduced-Form

	OLS	
	(1)	**(2)**
Panel A. Impact at One Year		
Angel/VC	-0.034	-0.034
	(0.025)	(0.030)
Survival	0.002	-0.021
	(0.053)	(0.054)
Has One Employee	0.023	-0.003
	(0.078)	(0.074)
log(#Web Flow)	0.628 0.969)	-0.167 (0.827)
Panel B. Impact at Two Years		
Angel/VC	-0.006	0.001
	(0.018)	(0.021)
Survival	-0.039	-0.072
	(0.088)	(0.089)
Has One Employee	0.013	-0.020
	(0.092)	(0.090)
log(#Web Flow)	0.937 (0.978)	0.640 (0.960)
Controls	No	Yes
Indicators for Application Rounds	Yes	Yes

Notes: This table presents OLS estimates of the impact of evaluator leniency instrument on venture outcomes. The sample includes all projects that are evaluated from the crowd spanning 2015-2018. 2SLS specification instrument for crowd-rating using an evaluator leniency measure that is estimated using data from other evaluations evaluated by a platform's user in the same year. All specifications control for application round fixed effects and observable characteristics. Standard errors are clustered at the project level.

Table 3.B.7 – Robustness Tests

	Feedback	Evaluator Interest	Evaluator Residualized	Evaluator Pooled	Evaluator Subsample	Bootstrap SE	Technology FEs	Additional Controls
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Panel A. Impact at One Year								
Angel/VC	-0.040	-0.064	-0.040	-0.029	-0.035	-0.040	-0.018	-0.036
	(0.046)	(0.056)	(0.046)	(0.045)	(0.054)	(0.040)	(0.046)	(0.045)
Survival	-0.024	-0.040	-0.024	0.019	0.059	-0.024	-0.032	-0.018
	(0.059)	(0.072)	(0.059)	(0.058)	(0.074)	(0.068)	(0.061)	(0.058)
Has one Employee	-0.005	-0.003	-0.004	0.035	-0.067	-0.004	0.002	0.017
	(0.088)	(0.106)	(0.088)	(0.086)	(0.115)	(0.099)	(0.090)	(0.085)
log(#Web Flow)	-0.200	-0.350	-0.202	0.866	1.975	-0.202	0.078	0.077
	(1.053)	(1.252)	(1.053)	(1.026)	(1.212)	(1.272)	(1.140)	(1.045)
Panel B. Impact at Two Years								
Angel/VC	0.002	0.009	0.001	-0.019	-0.036	0.001	0.027	0.005
	(0.040)	(0.053)	(0.040)	(0.038)	(0.036)	(0.029)	(0.043)	(0.038)
Survival	-0.082	-0.122	-0.084	-0.059	0.038	-0.084	-0.101	-0.072
	(0.090)	(0.119)	(0.090)	(0.084)	(0.101)	(0.107)	(0.097)	(0.087)
Has one Employee	-0.024	-0.025	-0.023	-0.002	-0.012	-0.023	-0.027	-0.012
	(0.103)	(0.137)	(0.104)	(0.097)	(0.112)	(0.107)	(0.109)	(0.099)
log(#Web Flow)	0.629	0.492	0.655	1.389*	2.655***	0.655	0.673	0.983
	(0.888)	(1.093)	(0.887)	(0.824)	(0.931)	(1.101)	(0.898)	(0.864)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Indicators for Application Round	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents robustness tests for my 2SLS estimates. The outcome is reported in each row. Column (1) controls for an indicator of whether ventures have received feedback on the online platform. Column (2) controls for an indicator of whether evaluators would be interested to invest in projects. Column (3) instruments the crowd-rating using the residualized leave-out leniency measure condition on application round fixed effects. Column (4) calculates the evaluator leniency measure using a leave-out leniency measure that is pooled across the application rounds. Column (5) calculates the evaluator leniency measure on a subsample of evaluators. Column (6) presents bootstrap-clustered standard errors from 200 replications. Finally, columns (7-8) controls for technology fixed effects and additional observable venture characteristics. All specifications control for application round fixed effects and observable characteristics. Standard errors are clustered at the project level.
* Significant at $p < 0.1$ *** Significant at $p < 0.01$

Table 3.B.8 – Weak Instrument Robust Inference

Dependent Variable	Angel/VC	Survival	Has One Employee	log(#Web Flow)
	(1)	**(2)**	**(3)**	**(4)**
Panel A. Impact at One Year				
Wald CI (95%)	[-0.113, 0.031]	[-0.152, 0.102]	[-0.179, 0.170]	[-2.178, 1.774]
Anderson-Rubin CI (95%)	[-0.121, 0.028]	[-0.166, 0.096]	[-0.196, 0.164]	[-2.685, 1.663]
Panel B. Impact at Two Years				
Wald CI (95%)	[-0.047, 0.051]	[-0.291, 0.153]	[-0.234, 0.187]	[-1.186, 2.498]
Anderson-Rubin CI (95%)	[-0.049, 0.053]	[-0.315, 0.119]	[-0.270, 0.172]	[-1.526, 2.372]

Note: This table presents robust inference test for a weak instrument. Panel A and B report confidence intervals using test inversion based on Anderson-Rubin statistic. All specification control for observable venture characteristics.

Table 3.B.9 – Coefficient Stability and Bias from Unobservables

	Baseline Effect (s.e.) [R^2]	Controlled Effect (s.e.) [R^2]	Identified Set			
			B&M	Oster	Oster	Conservative
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Angel/VC						
at One Year	0.014 (0.010) [0.10]	0.013 (0.012) [0.14]	[0.011, 0.013]	[0.011, 0.013]	[0.005, 0.013]	[-0.027, 0.013]
δ Ratio	–	–	4.7	4.7	1.5	0.3
at Two Years	0.009 (0.008) [0.07]	0.001 (0.010) [0.14]	[-0.006, 0.009]	[-0.003, 0.009]	[-0.019, 0.009]	[-0.102, 0.009]
δ Ratio	–	–	0.6	0.7	0.3	0.08

Notes: This table presents the estimated intervals for bias from omitted variables using the consistent estimator in the specification (11). Column (1) shows the baseline effect controlling for application round fixed effects only. Column (2) shows the controlled estimate, including observable characteristics used in specification (10). Column (3) shows the identified interval using Bellows and Miguel (2009) assumption on R_{max}, columns (4-5) using Oster (2019) assumption, and column (6) shows interval using a conservative R_{max} equal to one. In rows (2-4), I report the value of δ implying an estimated β equal to zero, conditional on R_{max}. Standard errors are clustered at the project level.

Table 3.B.10 – Crowd-Rating Impacts on Financing and Startup Outcomes: Nominal Score

Dependent Variable	Angel/VC		Survival		Has One Employee		log(#Web Flow)	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Panel A. Impact at One Year								
Score	0.010	0.009	0.063***	0.053***	0.050**	0.038*	0.774***	0.397*
	(0.008)	(0.009)	(0.016)	(0.015)	(0.021)	(0.023)	(0.250)	(0.219)
Obs.	500	461	467	461	453	447	206	203
R^2	0.010	0.13	0.04	0.21	0.06	0.19	0.07	0.36
Mean Dependent Variable	0.07	0.075	0.858	0.861	0.485	0.487	4.441	4.507
Panel B. Impact at Two Years								
Score	0.006	0.0006	0.033	0.038	0.053*	0.034	0.850***	0.633**
	(0.007)	(0.008)	(0.024)	(0.026)	(0.027)	(0.030)	(0.325)	(0.296)
Obs.	347	317	323	317	312	306	180	177
R^2	0.07	0.014	0.02	0.18	0.04	0.22	0.16	0.38
Mean Dependent Variable	0.04	0.041	0.755	0.760	0.445	0.447	4.027	4.096
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Indicators for Application Round	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the estimated coefficient β_1 from OLS of the impact of crowd-rating using the nominal score. The sample includes all projects that are evaluated from the crowd spanning 2015-2018. Outcomes in Panel A are an indicator equal to one when ventures experienced funding round over the next year (columns 1-4). In Panel B, outcomes are similar but measured over the next two years. All specifications control for application rounds fixed effects. Columns 2 and 4 add venture characteristics as control variables; estimated coefficients on this set are presented in Appendix Table 3.B.1. Standard errors are clustered at the project level.

3.B.3. Additional Figures

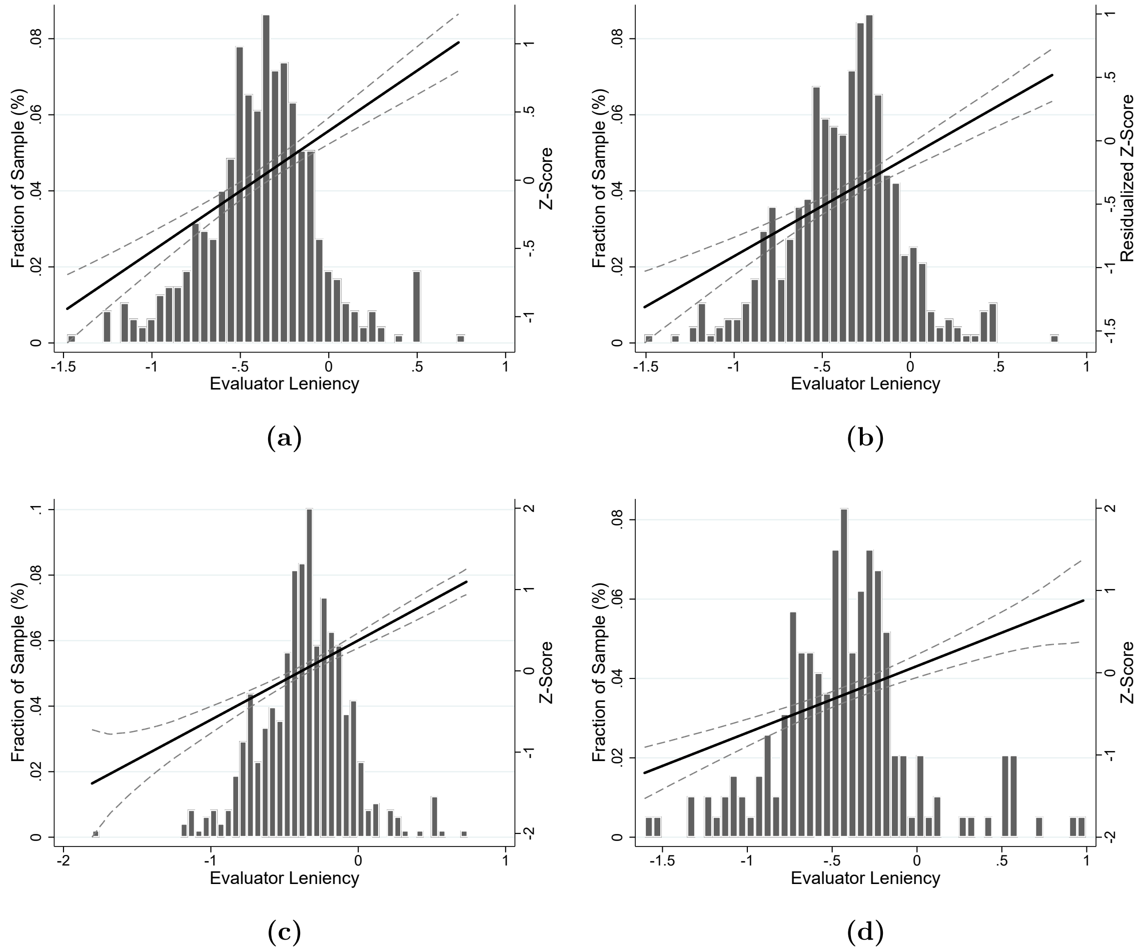
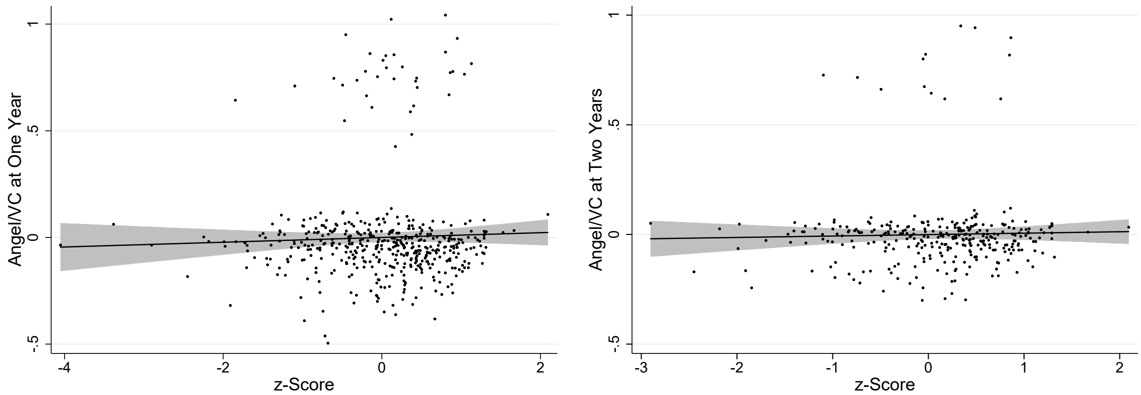


Figure 3.B.1 – Distribution and Impact of Evaluator Leniency on the Standardized Score.

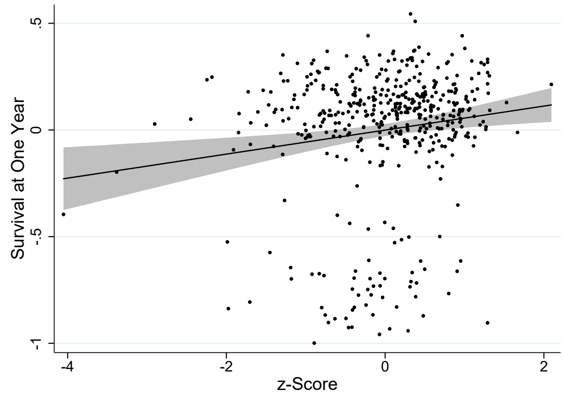
Notes: This figure shows the distribution of the evaluator leniency measure and the standardized score. Panel A shows the evaluator leniency measure that is estimated using data from other projects evaluated in the same year. Panel B shows the residualized evaluator leniency measure. Panel C shows the evaluator leniency measure pooled across the application rounds and Panel D shows the evaluator leniency measure that is estimated using data from a subsample of evaluators.



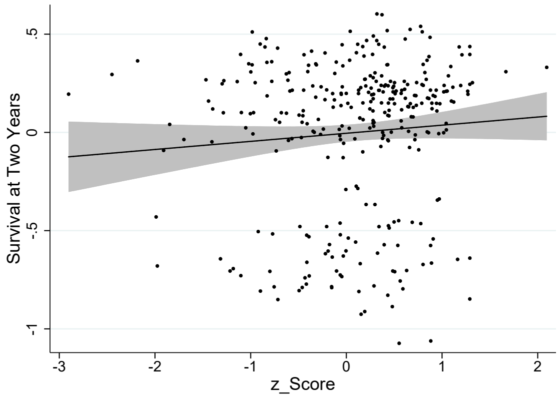
(a) **(b)**

Figure 3.B.2 – Financing Events and the Standardized Score.

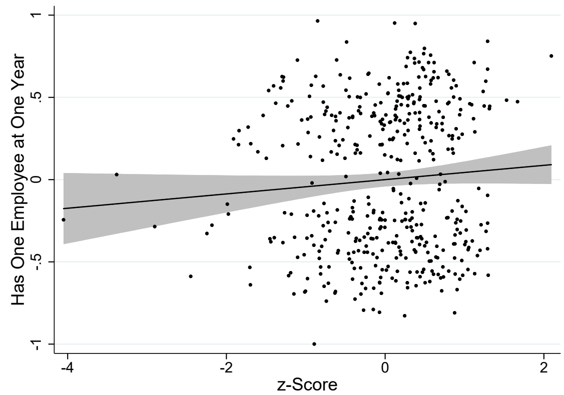
Notes: This figure presents the relationship between the residuals of subsequent financing events and the standardized score from the crowd. Panel A shows the relationship for the outcome measured at one year after the evaluation process while Panel B shows the outcome measured at two years. The residuals are estimated by regression onto the time-invariant venture characteristics and round applications fixed effects. Standard errors are clustered at the project level. 95 percent confidence intervals are shown.



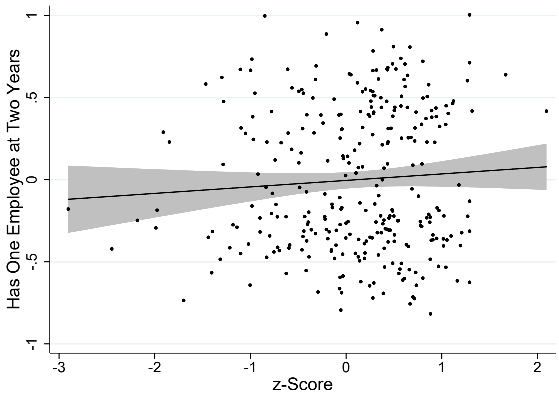
(a)



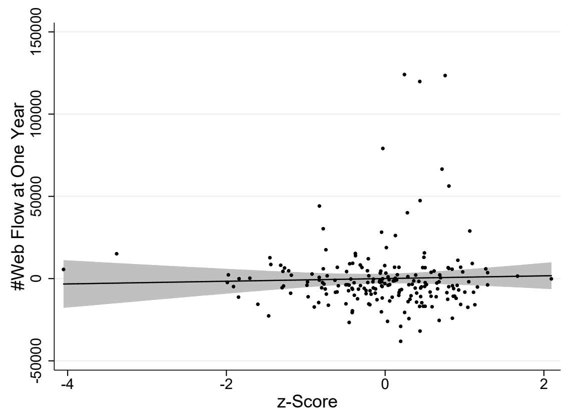
(b)



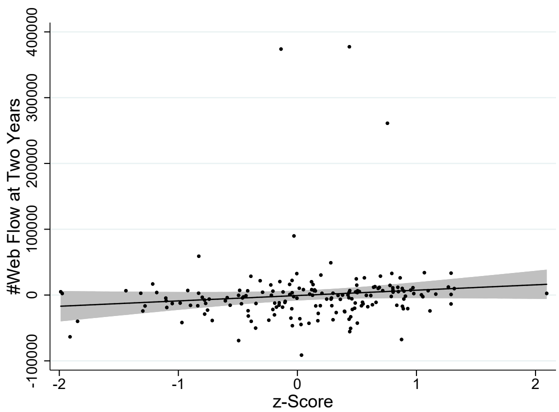
(c)



(d)



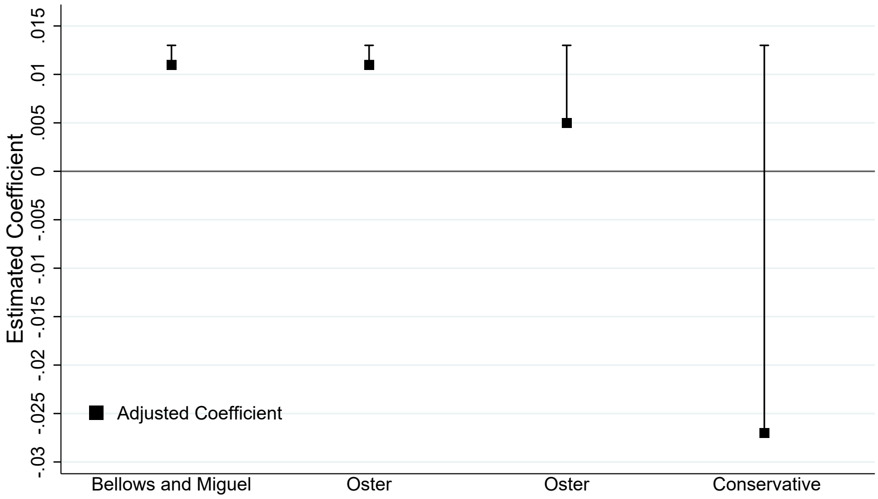
(e)



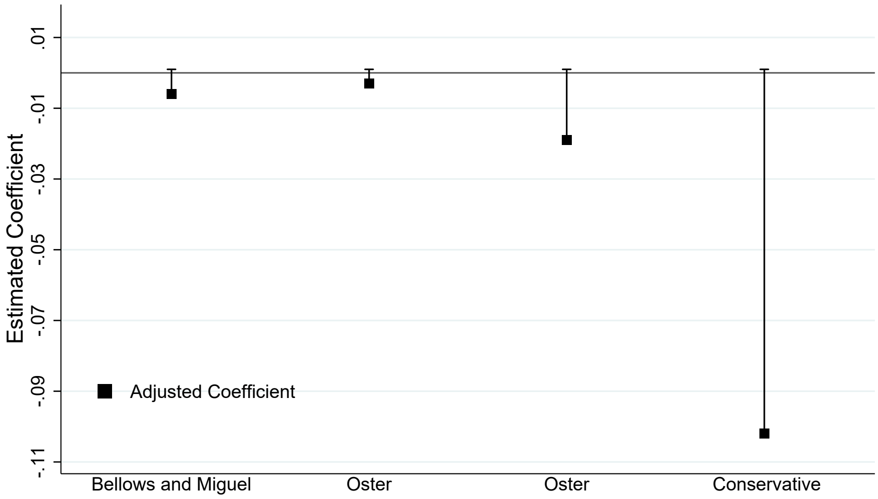
(f)

Figure 3.B.3 – Venture Outcomes and the Standardized Score.

Notes: This figure presents the relationship between the residuals of venture outcomes and the standardized score from the crowd. Panel A shows the relationship for the outcome measured at one year after the evaluation process while Panel B shows the outcome measured at two years. The residuals are estimated by regression onto the time-invariant venture characteristics and round applications fixed effects. Standard errors are clustered at the project level. 95 percent confidence intervals are shown.



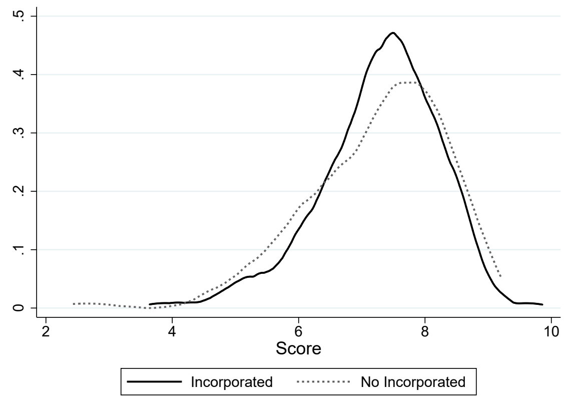
(a)



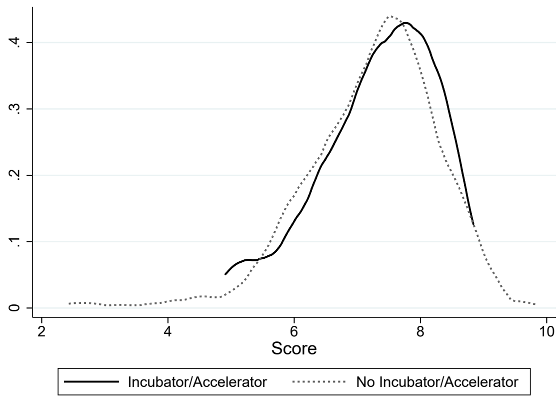
(b)

Figure 3.B.4 – Impacts of Crowd-rating on Financing.

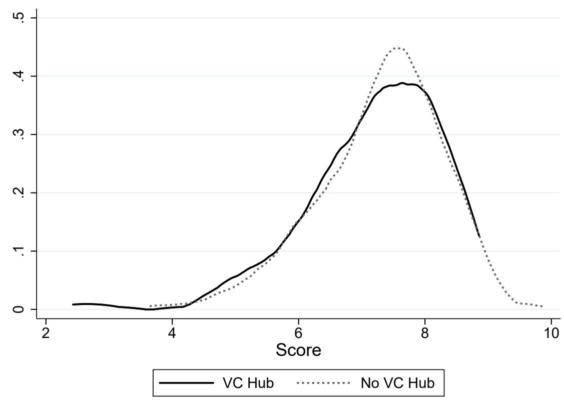
Note: This figure presents the estimated coefficient β_1 from specifications (10) and (11) using several assumptions for the R_{max}.



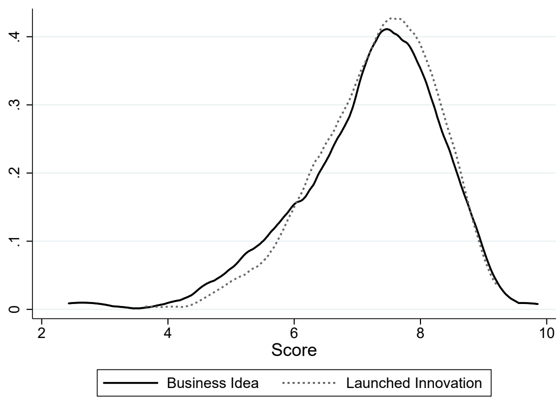
(a)



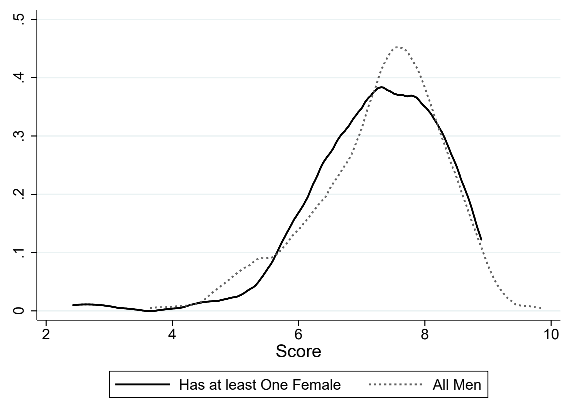
(b)



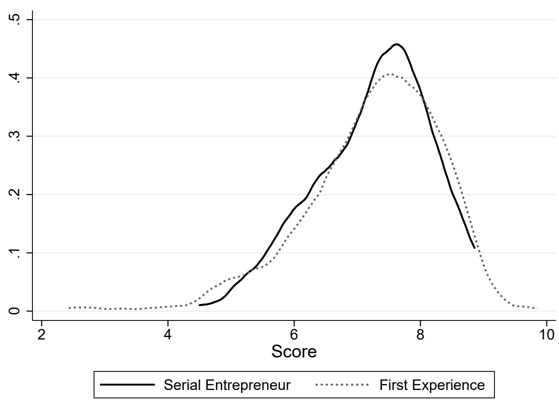
(c)



(d)



(e)



(f)

Figure 3.B.5 – Nominal Score by Heterogeneity Subsamples.

Note: This figure shows the nominal score split by heterogeneity subsamples used in the heterogeneity analysis in Table 3.4.

General Conclusion

To conclude this thesis, we propose a review of the main results and contributions obtained in the three chapters, with respect to the economic literature and the policy debates, as well as a discussion of their main limitations. We also outline directions for future research.

1 Main Results and Contributions

In a context where fostering economic growth is one of the primary objectives of policymakers, the contribution of innovation to productivity growth is often at the heart of the debate. This thesis aims to contribute to the economics of innovation literature on the consequences of market failures on both countries' and firms' innovation performances and the effectiveness of public and private interventions on research and innovation incentives. Do lessen regulations on domestic and foreign competition spur innovation intensity? Do public interventions and private initiatives reduce financing constraints?
This thesis seeks to evaluate each research question separately and shedding light new insights on the effect of competition and financing constraints.

1.1 Competition Regulation: The Importance of Domestic Competition

In the first chapter, we set out to study whether product market competition can foster innovation. More specifically, we investigate how innovation responds to a decrease in competition regulation, both domestic and foreign product market reform, and how they interplay. Changes in the degree of product market competition impact the overall economic performance in several ways, affecting the incentives firms face to engage in innovation activity, technological adoption and reallocation. However, the effect is ambiguous in the direction of incentives on firms' innovation, and aggregate economies. In our empirical analysis, we firstly compare the innovative response to the domestic and foreign market regulation across OECD countries.

The originality of this chapter is to evaluate the impacts of product market regulations, both domestic and foreign competition, on innovation intensity using a comprehensive dataset of 25 OECD countries over the 21 years from 1995 to 2015. Another novel contribution is the use in addition to standard econometric specifications, a graphical approach to causality, highlighting the relationship between domestic and foreign competition. This approach provide a understanding the interplay between the two types of regulation. We adopt an approach that relies on data rather than specifies a structural model to researcher discretion. Although this approach is static, one advantage of this identification approach is to process potential variables of interest together and allows us to explore interactions among them.

Consistent with previous evidence at both country and firm-level, we find that policies aiming to increase competition positively increase country-level innovation. In particular, we get that increasing competitive pressure from new entrants actually turns out to be a factor favoring innovation input and output, consistent with the argument of Arrow, which suggests a replacement effect. Using the graphical approach confirms that lessening market regulations positively influence innovation intensity at the country level. However, unlike our baseline results, we find that only regulation affecting domestic competitive pressure is directly related to an aggregate level of innovation. Moreover, we find that the regulation of foreign competition indirectly impacts on the innovation intensity by a profitable impact on domestic product market reforms. Our empirical results suggest that both regulations can be complementary factors to innovation and growth. Therefore, our results contribute to the understanding of the macro-economic reforms and how they interact, which are responsible for innovation incentives at the country level.

Main Limitations to Chapter 1

This chapter suffers from several limitations and interesting issues that can be addressed for future works. First, our analysis sample covers country-level data not allowing us to explore further mechanisms. We are at the limit of the use of a country-level panel dataset, and it is worth exploring industry variations and firm heterogeneities from more granular data. Second, our second identification strategy is static, leading to results that can be interpreted as a long-term response to regulatory changes. Therefore, we are unable to draw short-term estimates, while these changes are essential in understanding short-term impacts on innovation and mechanisms for policy subsequent implementation. Furthermore, our data prevent us to use dynamic panel data approach because of the lack of time variability in both regulation indicators spanning 1995-2015.

1.2 Financing Constraints: The Certification Role of Central Government

In the second chapter, we focus on the innovation performances of SMEs in the context of a European framework-program. More specifically, this chapter seeks to evaluate a more direct form of support: the first European R&D grant program that targets innovative SMEs. From a policy perspective, this program is interesting because is conceptualized on the U.S. Small Business Innovation Research program that provides financial support to early-stage ventures. Therefore, evaluating the effectiveness of public subsidies on innovation activities in European countries is relevant for policymakers to reduce financing frictions in small and young innovative firms. This chapter provides novel insight by leveraging a broad and comprehensive sample of small-and-medium sized firms over a large geographical dimension on a recent subsidy program.

In contrast to the existing literature on the evaluation of public subsidies that estimate the treatment effect on innovation inputs: R&D investments, employment level, or tangible investments, we assess the effect of R&D grants innovative outcomes. Examine the effectiveness of public incentives on innovation inputs might provide incomplete information, thus assessing the impact on innovation outputs is crucial. Innovation and technological changes are the primary objectives of public programs that support private R&D, therefore patent data can assess the rate of firms' capabilities and competitiveness. In addition, R&D efforts might remain constant even receiving a grant, inciting firms to improve R&D management or undertake collaborations (Bronzini and Piselli, 2016).

The main empirical challenge is that grants are not randomly assigned, therefore recipient and non-recipient firms could vary both in observable and unobservable characteristics that are likely to be correlated with outcomes. To overcome this challenge, we estimate the treatment effect by comparing recipient and potential non-recipient firms over time using propensity score matching and difference-in-differences estimator. This identification strategy allows us to control for treatment endogeneity and potential selection bias in grant assignment. We find that the public program significantly increases on average innovation output. More specifically, Phase I award that subsidized proof-of-concept research increases subsequent patent applications. This positive effect of the program is due to both intensive and extensive margins, suggesting that not only firms already engaged in innovative activities are impacted but also impacts the probability of patenting for firms without previous patent applications. Thus, the proof-of-concept grant crowd in private R&D investments. In contrast, the Phase II award that subsidized later development stage (i.e., demonstration, and prototype) has no sizeable effect on innovation performance, suggesting that the program fails to reduce underinvestment in R&D (i.e., maximize social welfare). However, this later stage is dedicated to funding long-term investments, aiming to promote the commercialization of highly innovative research. Heterogeneity analysis suggests that young innovative firms are more responsive to the R&D grant than larger firms, which is consistent with the direct funding reducing financing constraints.

The results from this chapter highlight the need to take into account heterogeneity in firm characteristics, as suggested by previous evidence (Bronzini and Piselli, 2016). We provide suggestive evidence that the proof-of-concept grants ease financing constraints by signaling firms' quality to potential external investors. In particular, recipient firms increase the probability and the amount of receiving subsequent debt financing. Beyond this mechanism that drives our results, this chapter highlights that young innovative firms in Europe face severe information frictions, which could impede both technological capabilities and the high growth potential of this subpopulation.

This chapter has policy implications for programs that target SMEs. The results suggest that the program is effective by implementing proof-of-concept grants with a smaller amount of public funding instead of larger grants dedicated to both development and commercialization stages, which is consistent with the U.S program (Howell, 2017). Furthermore, overall innovation performance and growth could be improved by targeting younger firms.

Main Limitations to Chapter 2

It is worth reminding that this chapter suffers from several limitations and that interesting issues can be addressed for future researches. Due to several data limitations, the scope of the results highlighted in Chapters 2 should be nuanced. First, we are unable to exploit confidential data on small-and-medium-sized European firms that apply for each competition (i.e., Phase I and II). Therefore, we only observed firms that win a grant in 2014 but do not observe firms that do not pass eligibility conditions to receive a grant. Although, we rely on matching strategy to construct a control group based on pre-treatment observable characteristics from a random sample of innovative firms. However, this approach raises the concern that the applicant pool might have potential time-varying unobserved characteristics (i.e., application decisions and the cost of application) compared to the matched group. This selection bias or "picking-the-winner" challenges evidence on the causal impacts of R&D grants, which might lead to biased estimates. Reassuringly, even our analysis sample rely on recipient firms and a matched control group providing information, the positive effect on the intensive and extensive margins for Phase I is highly similar in magnitude than quasi-experimental results from a regression discontinuity design (RDD) provide by Santoleri et al. (2020). Related to this data limitation, our analysis sample does not allow us to examine the knowledge production function. We are unable to recover R&D spending at the firm-level for the period 2008-2017, and thus prevent us from exploring the return of R&D investments as mechanisms behind the positive average effect on proof-of-concept grants. Is an increase in R&D spending that causally affects the innovation outcomes? Or it is a mix of existing knowledge stock and the co-existence of other public policies? Is the subsidy program reduce effectively the user cost of capital? This calls for future data collection (i.e., administrative) to carefully take into account this relationship.

1.3 Information Frictions: Difficulty in Assessment of Early-stage Ventures

In the third chapter, we focus on an online platform that provides information on early-stage ventures. More specifically, this chapter seeks to evaluate whether early-stage investors are impacted by an assessment from the crowd about venture quality and how this information could affect investment decision-making. Reducing information frictions between investors and entrepreneurs is crucial for financing and nurturing of high growth business ideas and technological changes. Over the last decade, the uncertainty that affects the screening process of early-stage investors has grown because of the declining barriers to venture entry. Therefore, investigating the role of new intermediaries have predictive power for subsequent success is relevant, both for potential investors and entrepreneurs themselves.

We motivate our analysis using a simple statistical extraction model in which the crowd assesses ventures' quality based on observable characteristics of projects and their founders. We assume that the crowd has a signaling mechanism on quality disclosure to potential investors, reducing information frictions. Thus, the model predicts that higher-scoring from the crowd produces a valuable signal and alleviates information asymmetries. This prediction is intuitive but never has been empirically investigated in the context of a crowd-rating platform. However, providing evidence on the causal effects of crowd-rating is challenging. This chapter overcomes identification challenges, offering new insights into how new intermediaries affect subsequent venture success.

The key to our research design is that we leverage quasi-random variation in evaluators' leniency assessment to control for endogeneity issues. Using this appropriate research design, we find no statistically significant impacts on ventures' subsequent financing from early-stage investors, survival, and whether ventures have at least one employee both in the short and medium-run. These results suggest that potential investors do not learn from the crowd, failing to reduce information frictions. One exception is the heterogeneous impact on venture survival conditionally to the project development stage. This result suggests that the primary mechanism for this effect is that founders update their priors due to external signals about their project quality. Therefore, new information from the crowd could determine abandonment or continuation decisions.

Taken together, the contribution of this chapter is to show that assessing and screening of high growth potential ideas is tough, even from new intermediaries such as the crowd. Finally, this chapter shows that is essential to address endogeneity issues. Ignoring bias due to selection on unobservables could lead to a wrong conclusion on the impact of the information reveals by an online platform.

Main Limitations to Chapter 3

Our identification strategy leverage random variation in the score that quasi-random evaluators assign to projects. We use this exogenous variation to examine the effect of a crowd-rating platform on subsequent financing, but there remain important limitations to the data and interpretation of the results. First, Chapter 3 provides an original dataset that are never been explored in the literature but with the limitation that our results are limited to a small sample of entrepreneurial ideas or early-stage ventures located in France. This emphasizes the importance of interpreting the results with caution due to data representativeness to the overall population of entrepreneurs. However, information on ventures before their first investment round is scarce, raising empirical challenges to assess the representativeness of our sample, and thus generalize our findings. A second limitation is that our results provide estimates for a subset of projects for whom the evaluator interest matters, and consequently the stringency of evaluators. For example, we are unable to estimate the effect for projects that are not rated on the online platform or projects that are unaffected by evaluators leniency (or stringency) due to bad (or good) business ideas. The subpopulation of projects that we expect to be responsive to the instrument may be a subpopulation of ventures with ideas of intermediate quality compared to the overall population of projects launched on the online platform.

2 Research Agenda

Based on and beyond empirical studies proposed in this thesis and the main limitations mentioned previously, I also emphasize the future research agenda on the intersection between the economics of innovation and entrepreneurial finance. First, based on the second chapter of this thesis, I would like to expand the evaluation of place-based policies that subsidies private firms, and ultimately generate aggregate growth in target areas. The evaluation literature has focused on the impact of such policies on recipient firms through several firm-level outcomes. However, place-based policies might lead to spillovers to non-recipient firms both within and outside target areas (Neumark and Simpson, 2015). Relaxing the Stable Unit Treatment Value Assumption (SUTVA) - treatment to one population does not impact outcomes of other population- will offer an appealing examination of spillover effects on potential interacting firms.

Second, related to spillovers, examining the relationship between firms' productivity and knowledge spillovers would be interesting. While empirical studies (e.g., Griliches 1992, Bloom et al. 2013) have highlighted the knowledge diffusion through patents, only a few proportions of innovative firms patent ideas. Therefore, it would be interesting to extend our comprehension of worker mobility as other mechanisms of knowledge transfers among (competitive) firms and how these impact on productivity.

Finally, I plan to extend my analyses to Chapter 3 using a new principal agent of bias model in which evaluators discriminate between projects on the basis of gender. Women entrepreneurs are under-represented in high-growth firms and are at a disadvantage in raising external capital. For example, in the U.S., 10 to 15 percent of founders, out of a population of 30 percent, succeed in raising private capital. Recent studies using quasi-random judges to identify discrimination have taken a valuable step towards solid identification.

Bibliography

Abadie, A. (2005). Semiparametric difference-in-differences estimators. *The Review of Economic Studies*, 72(1):1–19. 86, 105

Abramovitz, M. et al. (1991). Thinking about growth. *Cambridge Books*. 1

Acharya, V. V., Baghai, R. P., and Subramanian, K. V. (2013). Labor Laws and Innovation. *The Journal of Law and Economics*, 56(4):997–1037. 34

Aghion, P., Askenazy, P., Bourlès, R., Cette, G., and Dromel, N. (2009). Education, Market Rigidities and Growth. *Economics Letters*, 102(1):62–65. 1, 33

Aghion, P., Bergeaud, A., Lequien, M., and Melitz, M. J. (2017). The Impact of Exports on Innovation : Theory and Evidence. *NBER Working Paper*, pages 1–33. 31, 32, 34

Aghion, P., Bloom, N., Blundell, R., Griffith, R., and Howitt, P. (2005). Competition and Innovation: An Inverted-U Relationship. *The Quarterly Journal of Economics*, 120(2):701–728. 16, 27, 28, 30, 32, 38, 39, 40, 43

Aghion, P., Harris, C., Howitt, P., and Vickers, J. (2001). Competition, Imitation and Growth with Step-by-Step Innovation. *The Review of Economic Studies*, 68(3):467–492. 8

Aghion, P. and Howitt, P. (1992). A Model of Growth through Creative Destruction. *Econometrica*, 60(2). 8, 14, 27

Aghion, P. and Howitt, P. (1998). A Schumpeterian Perspective on Growth and Competition. In *New Theories in Growth and Development*, pages 9–49. Springer. 27, 31, 40

Agrawal, A., Rosell, C., and Simcoe, T. (2020). Tax Credits and Small Firm R&D Spending. *American Economic Journal: Economic Policy*, 12(2):1–21. 96

Aigner, D. J. and Cain, G. G. (1977). Statistical Theories of Discrimination in Labor Markets. *ILR Review*, 30(2):175–187. 115, 130, 134

Aizer, A. and Doyle Jr, J. J. (2015). Juvenile Incarceration, Human Capital, and Future Crime: Evidence from Randomly Assigned Judges. *The Quarterly Journal of Economics*, 130(2):759–803. 116, 138

Akcigit, U. and Ates, S. T. (2019). What Happened to US Business Dynamism? Technical report, National Bureau of Economic Research. 9, 15

Akcigit, U. and Kerr, W. R. (2018). Growth through Heterogeneous Innovations. *Journal of Political Economy*, 126(4):1374–1443. 31

Akerlof, G. (1970). The Market for 'lemons': Quality Uncertainty and the Market Mechanism. *Quarterly Journal of Economics*, 84(3):488–500. 14

Altonji, J. G., Elder, T. E., and Taber, C. R. (2005). Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools. *Journal of political economy*, 113(1):151–184. 116, 148

Altonji, J. G. and Pierret, C. R. (2001). Employer Learning and Statistical Discrimination. *The Quarterly Journal of Economics*, 116(1):313–350. 134

Anderson, M. and Magruder, J. (2012). Learning from the Crowd: Regression Discontinuity Estimates of the Effects of an Online Review Database. *The Economic Journal*, 122(563):957–989. 119

Andrews, D. and Cingano, F. (2014). Public Policy and Resource Allocation: Evidence from Firms in OECD Countries. *Economic Policy*, 29(78):253–296. 30

Andrews, D. and Criscuolo, C. (2013). Knowledge-based Capital, Innovation and Resource Allocation. *OECD*. 15, 29

Andrews, I., Stock, J. H., and Sun, L. (2019). Weak Instruments in Instrumental Variables Regression: Theory and Practice. *Annual Review of Economics*, 11:727–753. 148

Angrist, J. D., Graddy, K., and Imbens, G. W. (2000). The Interpretation of Instrumental Variables Estimators in Simultaneous Equations Models with an Application to the Demand for Fish. *The Review of Economic Studies*, 67(3):499–527. 137, 138

Angrist, J. D. and Krueger, A. B. (2001). Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments. *Journal of Economic Perspectives*, 15(4):69–85. 43

Arrow, K. (1962a). Economic Welfare and the Allocation of Resources for Invention. Technical report, National Bureau of Economic Research, Inc. 15, 16

Arrow, K. J. (1962b). The Economic Implications of Learning by Doing. *The Review of Economic Studies*, 29(3):155–173. 9, 10, 16, 27, 49, 67

Ashenfelter, O. (1978). Estimating the Effect of Training Programs on Earnings. *The Review of Economics and Statistics*, pages 47–57. 88

Åstebro, T. and Elhedhli, S. (2006). The Effectiveness of Simple Decision Heuristics: Forecasting Commercial Success for Early-stage Ventures. *Management Science*, 52(3):395–409. 118, 154

Autor, D. H., Dorn, D., and Hanson, G. H. (2016). The China Shock: Learning from Labor Market Adjustment to Large Changes in Trade. Working Paper 21906, National Bureau of Economic Research. 15, 16, 31

Ayyagari, M., Demirgüç-Kunt, A., and Maksimovic, V. (2008). How Important are Financing Fonstraints? the Role of Finance in the Business Environment. *The World Bank Economic Review*, 22(3):483–516. 43, 45

Ayyagari, M., Demirguc-Kunt, a., and Maksimovic, V. (2013). What Determines Protection of Property Rights? An Analysis of Direct and Indirect Effects. *Journal of Financial Econometrics*, 11(4):610–649. 45, 46

Barkai, S. (2016). Declining Labor and Capital Shares. *The Journal of Finance*. 15

Barro, R. J. (1991). Economic Growth in a Cross Section of Countries. *The Quarterly Journal of Economics*, 106(2):407–443. 45

Barro, R. J. and Sala-i Martin, X. (1992). Convergence. *Journal of Political Economy*, 100(2):223–251. 8

Barro, R. J. and Sala-i Martin, X. I. (2003). *Economic growth*. MIT press. 8

Becker, B. (2015). Public R&D Policies and Private R&D Investment: A Survey of the Empirical Evidence. *Journal of Economic Surveys*, 29(5):917–942. 68

Becker, G. (1957). The Economics of Discrimination. 130

Becker, S. O., Egger, P. H., and Von Ehrlich, M. (2013). Absorptive Capacity and the Growth and Investment Effects of Regional Transfers: A Regression Discontinuity Design with Heterogeneous Treatment Effects. *American Economic Journal: Economic Policy*, 5(4):29–77. 66

Bellows, J. and Miguel, E. (2009). War and Local Collective Action in Sierra Leone. *Journal of Public Economics*, 93(11-12):1144–1157. 117, 148, 149, 175

Bena, J. and Simintzi, E. (2016). Labor-induced Technological Change: Evidence from Doing Business in China. 16

Bergeaud, A., Cette, G., and Lecat, R. (2016). Productivity Trends in Advanced Countries between 1890 and 2012. *Review of Income and Wealth*, 62(3):420–444. 1, 2

Bernstein, S., Giroud, X., and Townsend, R. R. (2016). The Impact of Venture Capital Monitoring. *The Journal of Finance*, 71(4):1591–1622. 18, 142

Bernstein, S., Korteweg, A., and Laws, K. (2017). Attracting Early-stage Investors: Evidence from a Randomized Field Experiment. *The Journal of Finance*, 72(2):509–538. 115, 128, 129, 145

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How Much Should We Trust Differences-in-Differences Estimates? *The Quarterly Journal of Economics*, 119(1):249–275. 81, 87

Bhuller, M., Dahl, G. B., Løken, K. V., and Mogstad, M. (2020). Incarceration, Recidivism, and Employment. *Journal of Political Economy*, 128(4):1269–1324. 116, 148, 155

Blind, K. (2012). The Influence of Regulations on Innovation: A Quantitative Assessment for OECD Countries. *Research Policy*, 41(2):391–400. 29, 30

Bloom, N., Draca, M., and Van Reenen, J. (2016). Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity. *The Review of Economic Studies*, 83(1):87–117. 16, 28, 31, 32, 41

Bloom, N., Schankerman, M., and Van Reenen, J. (2013). Identifying Technology Spillovers and Product Market Rivalry. *Econometrica*, 81(4):1347–1393. 12, 189

Bloom, N., Van Reenen, J., and Williams, H. (2019). A Toolkit of Policies to Promote Innovation. *Journal of Economic Perspectives*, 33(3):163–84. 3, 5, 9, 10, 14, 15

Blundell, R. and Costa Dias, M. (2000). Evaluation Methods for Non-experimental Data. *Fiscal Studies*, 21(4):427–468. 78

Blundell, R., Griffith, R., and Van Reenen, J. (1999). Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms. *The Review of Economic Studies*, 66(3):529–554. 28

Blundell, R., Griffith, R., Van Reenen, J., et al. (1993). Knowledge Stocks, Persistent Innovation and Market Dominance: Evidence from a Panel of British Manufacturing Firms. Technical report, Institute for Fiscal Studies. 30

Boeing, P. (2016). The Allocation and Effectiveness of China's R&D Subsidies - Evidence from Listed Firms. *Research Policy*, 45(9):1774–1789. 78

Bohren, J. A., Imas, A., and Rosenberg, M. (2019). The Dynamics of Discrimination: Theory and Evidence. *American Economic Review*, 109(10):3395–3436. 130, 131, 134

Boltho, A. (1982). *The European Economy: Growth and Crisis*. Oxford University Press, USA. 3

Bordalo, P., Coffman, K., Gennaioli, N., and Shleifer, A. (2016). Stereotypes*. *The Quarterly Journal of Economics*, 131(4):1753–1794. 134

Borusyak, K. and Jaravel, X. (2017). Revisiting Event Study Designs. 74

Bourlès, R., Cette, G., Lopez, J., Mairesse, J., and Nicoletti, G. (2013). Do Product Market Regulations In Upstream Sectors Curb Productivity Growth? Panel Data Evidence For OECDCountries. *The Review of Economics and Statistics*, 95(5):1750–1768. 29, 30, 34

Bozio, A., Irac, D., and Py, L. (2014). Impact of Research Tax Credit on R&D and Innovation: Evidence from the 2008 French Reform. 6

Branstetter, L. G. and Sakakibara, M. (2002). When Do Research Consortia Work Well and Why? Evidence from Japanese Panel Data. *American Economic Review*, 92(1):143–159. 12

Breusch, T., Ward, M. B., Nguyen, H. T. M., and Kompas, T. (2011). FEVD: Just IV or Just Mistaken? *Political Analysis*, pages 165–169. 39

Bronzini, R. and de Blasio, G. (2006). Evaluating the Impact of Investment Incentives: The Case of Italy's Law 488/1992. *Journal of Urban Economics*, 60(2):327–349. 66

Bronzini, R. and Iachini, E. (2014). Are incentives for R&D effective? Evidence from a Regression Discontinuity Approach. *American Economic Journal: Economic Policy*, 6(4):100–134. 17, 68, 69, 70, 74, 81, 97

Bronzini, R. and Piselli, P. (2016). The Impact of R&D Subsidies on Firm Innovation. *Research Policy*, 45(2):442–457. 17, 69, 74, 75, 81, 84, 91, 96, 97, 185, 186

Buccirossi, P., Ciari, L., Duso, T., Spagnolo, G., and Vitale, C. (2013). Competition Policy and Productivity Growth: An Empirical Assessment. *Review of Economics and Statistics*, 95(4):1324–1336. 34, 43

Byrne, D. M., Fernald, J. G., and Reinsdorf, M. B. (2016). Does the United States have a productivity slowdown or a measurement problem? *Brookings Papers on Economic Activity*, 2016(1):109–182. 3

Cabral, L. and Hortacsu, A. (2010). The Dynamics of Seller Reputation: Evidence from eBay. *The Journal of Industrial Economics*, 58(1):54–78. 119

Calligaris, S., Del Gatto, M., Hassan, F., Ottaviano, G. I., and Schivardi, F. (2018). The Productivity Puzzle and Misallocation: an Italian Perspective. *Economic Policy*, 33(96):635–684. 15

Canton, E., Ciriaci, D., Solera, I., et al. (2014). The Economic Impact of Professional Services Liberalisation. Technical report, Directorate General Economic and Financial Affairs (DG ECFIN), European Commission. 16, 30

Cao, R. (2020). Crowd-Based Rankings and Frictions in New Venture Finance. Technical report, National Bureau of Economic Research. 118, 156

Carpenter, R. E. and Petersen, B. C. (2002). Is The Growth of Small Firms Constrained by Internal Finance? *Review of Economics and Statistics*, 84(2):298–309. 68, 91, 93

Catalini, C., Guzman, J., and Stern, S. (2019). Hidden in Plain Sight: Venture Growth With or Without Venture Capital. Technical report, National Bureau of Economic Research. 135

Cerqua, A. and Pellegrini, G. (2014). Do Subsidies to Private Capital Boost Firms' Growth? A Multiple Regression Discontinuity Design Approach. *Journal of Public Economics*, 109:114–126. 64

Cette, G., Lopez, J., and Mairesse, J. (2017). Upstream Product Market Regulations, ICT, R&D and Productivity. *Review of Income and Wealth*, 63:S68–S89. 34

Chen, M. X. and Wu, M. (Forthcoming). The Value of Reputation in Trade: Evidence from Alibaba. *The Review of Economics and Stattistics*. 119

Chen, Y. (2018). User-Generated Physician Ratings: Evidence from Yelp. Technical report. 115, 137

Chen, Z., Liu, Z., Suárez Serrato, J. C., and Xu, D. Y. (2018). Notching R&D Investment with Corporate Income Tax Cuts in China. Technical report, National Bureau of Economic Research. 17

Chetty, R., Looney, A., and Kroft, K. (2009). Salience and Taxation: Theory and Evidence. *American Economic Review*, 99(4):1145–77. 81, 87

Chevalier, J. A. and Mayzlin, D. (2006). The Effect of Word of Mouth on Sales: Online Book Reviews. *Journal of Marketing Research*, 43(3):345–354. 119

Cincera, M., Ravet, J., and Veugelers, R. (2016). The Sensitivity of R&D Investments to Cash Flows: Comparing Young and Old EU and US Leading Innovators. *Economics of Innovation and new technology*, 25(3):304–320. 13

Ciriaci, D., Grassano, N., Vezzani, A., et al. (2016). Regulation, Red Tape and Location Choices of Top R&D Investors. Technical report, Directorate General Economic and Financial Affairs (DG ECFIN), European Commission. 16, 29

Cockburn, I. M. and Henderson, R. M. (1998). Absorptive Capacity, Coauthoring Behavior, and the Organization of Research in Drug Discovery. *The Journal of Industrial Economics*, 46(2):157–182. 12

Coe, D. T. and Helpman, E. (1995). International R&D Spillovers. *European Economic Review*, 39(5):859 – 887. 16, 31, 58

Coelli, F., Moxnes, A., and Ulltveit-Moe, K. H. (2016). Better, Faster, Stronger: Global Innovation and Trade Liberalization. Technical report, National Bureau of Economic Research. 31

Cohen, S. and Hochberg, Y. V. (2014). Accelerating Startups: The Seed Accelerator Phenomenon. 18

Cohen, W. M. (2010). Chapter 4 - Fifty Years of Empirical Studies of Innovative Activity and Performance. In Hall, B. H. and Rosenberg, N., editors, *Handbook of The Economics of Innovation, Vol. 1*, volume 1 of *Handbook of the Economics of Innovation*, pages 129 – 213. North-Holland. 27

Cohen, W. M. and Levinthal, D. A. (1989). Innovation and Learning: The Two Faces of R & D. *The Economic Journal*, 99(397):569–596. 12

Colombo, M. G., Grilli, L., and Murtinu, S. (2011). R&D Subsidies and the Performance of High-tech Start-ups. *Economics Letters*, 112(1):97–99. 68, 69, 94

Cornelli, F. (1996). Optimal Selling Procedures with Fixed Costs. *Journal of Economic Theory*, 71(1):1–30. 122

Corrado, C., Haskel, J., Jona-Lasinio, C., and Iommi, M. (2012). Intangible Capital and Growth in Advanced Economies: Measurement Methods and Comparative Results. Technical report, Discussion Paper series, Forschungsinstitut zur Zukunft der Arbeit. 27

Corrado, C., Haskel, J., Jona-Lasinio, C., and Iommi, M. (2013). Innovation and Intangible Investment in Europe, Japan, and the United States. *Oxford Review of Economic Policy*, 29(2):261–286. 6, 7

Corrado, C., Haskel, J., Jona-Lasinio, C., and Iommi, M. (2016). Intangible Investment in the EU and US before and since the Great Recession and its Contribution to Productivity Growth. Technical report, EIB Working Papers. 7

Corrado, C., Hulten, C., and Sichel, D. (2005). Measuring Capital and Technology: An Expanded Framework. In *Measuring capital in the new economy*, pages 11–46. University of Chicago Press. 7

Criscuolo, C., Martin, R., Overman, H. G., and Van Reenen, J. (2019). Some Causal Effects of an Industrial Policy. *American Economic Review*, 109(1):48–85. 66, 90, 91, 97

Cusolito, A. P., Dautovic, E., and McKenzie, D. (2020). Can Government Intervention Make Firms More Investment-Ready? A Randomized Experiment in the Western Balkans. *Review of Economics and Statistics*, pages 1–45. 120, 157

Czarnitzki, D. and Lopes-Bento, C. (2013). Value for Money? New Microeconometric Evidence on Public R&D Grants in Flanders. *Research Policy*, 42(1):76–89. 86

Czarnitzki, D. and Lopes-Bento, C. (2014). Innovation Subsidies: Does the Funding Source Matter for Innovation Intensity and Performance? Empirical Evidence from Germany. *Industry and Innovation*, 21(5):380–409. 69

Dahl, G. B., Kostøl, A. R., and Mogstad, M. (2014). Family Welfare Cultures. *The Quarterly Journal of Economics*, 129(4):1711–1752. 138, 139, 155

Dalle, J., den Besten, M., and Menon, C. (2017). Using Crunchbase for Economic and Managerial Research. Technical report, OECD. 124

Dasgupta, P. and Stiglitz, J. (1980). Industrial Structure and the Nature of Innovative Activity. *The Economic Journal*, 90(358):266–293. 27

David, P. A., Hall, B. H., and Toole, A. A. (2000). Is Public R&D a Complement or Substitute for Private R&D? A Review of the Econometric Evidence. *Research policy*, 29(4-5):497–529. 17, 68, 69

Decker, R. A., Haltiwanger, J., Jarmin, R. S., and Miranda, J. (2016). Declining Business Dynamism: What We Know and the Way Forward. *American Economic Review*, 106(5):203–07. 15

Di Tella, R. and Schargrodsky, E. (2013). Criminal Recidivism After Prison and Electronic Monitoring. *Journal of Political Economy*, 121(1):28–73. 116

Dixit, A. K. and Stiglitz, J. E. (1977). Monopolistic Competition and Optimum Product Diversity. *The American Economic Review*, 67(3):297–308. 27

Dobbie, W., Goldin, J., and Yang, C. S. (2018). The Effects of Pretrial Detention on Conviction, Future Crime, and Employment: Evidence from Randomly Assigned Judges. *American Economic Review*, 108(2):201–40. 116, 137, 155

Dorn, D., Katz, L. F., Patterson, C., Van Reenen, J., et al. (2017). Concentrating on the Fall of the Labor Share. *American Economic Review*, 107(5):180–85. 15

Doyle Jr, J. J., Graves, J. A., Gruber, J., and Kleiner, S. A. (2015). Measuring Returns to Hospital Care: Evidence from Ambulance Referral Patterns. *Journal of Political Economy*, 123(1):170–214. 141, 155

Edquist, C. (1997). *Systems of Innovation: Technologies, Institutions, and Organizations*. Psychology Press. 10

Égert, B. (2016). Regulation, Institutions, and Productivity: New Macroeconomic Evidence from OECD Countries. *American Economic Review*, 106(5):109–13. 34

Einiö, E. (2014). R&D Subsidies and Company Performance: Evidence from Geographic Variation in Government Funding based on the ERDF Population-density Rule. *Review of Economics and Statistics*, 96(4):710–728. 17

Ellman, M. and Hurkens, S. (2019). Optimal Crowdfunding Design. *Journal of Economic Theory*, 184:104939. 122

Ewens, M., Nanda, R., and Rhodes-Kropf, M. (2018). Cost of Experimentation and the Evolution of Venture Capital. *Journal of Financial Economics*, 128(3):422–442. 18, 114, 118, 119

Ewens, M. and Townsend, R. R. (2020). Are Early Stage Investors Biased Against Women? *Journal of Financial Economics*, 135(3):653–677. 134, 151

Fafchamps, M. and Woodruff, C. (2016). *Identifying Gazelles: Expert Panels vs. Surveys as a Means to Identify Firms with Rapid Growth Potential*. The World Bank. 114, 118, 120

Farronato, C., Fradkin, A., Larsen, B., and Brynjolfsson, E. (2020). Consumer Protection in an Online World: An Analysis of Occupational Licensing. Technical report, National Bureau of Economic Research. 115, 137

Freyaldenhoven, S., Hansen, C., and Shapiro, J. M. (2019). Pre-event Trends in the Panel Event-study Design. *American Economic Review*, 109(9):3307–38. 74

Garcia-Macia, D., Hsieh, C.-T., and Klenow, P. J. (2019). How Destructive is Innovation? *Econometrica*, 87(5):1507–1541. 9

Gilbert, R. (2006). Looking for Mr. Schumpeter: Where Are We in the Competition–Innovation Debate? *Innovation Policy and the Economy*, 6:159–215. 15, 27

Gilbert, R. J. and Newbery, D. M. (1982). Preemptive Patenting and the Persistence of Monopoly. *The American Economic Review*, pages 514–526. 27

Goldschlag, N. and Tabarrok, A. (2018). Is Regulation to Blame for the Decline in American Entrepreneurship? *Economic Policy*, 33(93):5–44. 30

Gompers, P. and Lerner, J. (2001). The Venture Capital Revolution. *Journal of economic perspectives*, 15(2):145–168. 18, 114, 132

Gompers, P. A., Gornall, W., Kaplan, S. N., and Strebulaev, I. A. (2020). How Do Venture Capitalists Make Decisions? *Journal of Financial Economics*, 135(1):169–190. 130, 157

Gonzalez, F. and Miguel, E. (2015). War and Local Collective Action in Sierra Leone: A Comment on the Use of Coefficient Stability Approaches. *Journal of Public Economics*, 128:30–33. 117, 149

Gonzalez-Uribe, J. and Leatherbee, M. (2018). The Effects of Business Accelerators on Venture Performance: Evidence from Start-up Chile. *The Review of Financial Studies*, 31(4):1566–1603. 19, 114, 123

Gonzalez-Uribe, J. and Reyes, S. (2019). Identifying and Boosting 'Gazelles': Evidence from Business Accelerators. *Available at SSRN 3478290*. 19, 156

Gordon, R. J. (2012). Is US Economic Growth Over? Faltering Innovation Confronts the Six Headwinds. Technical report, National Bureau of Economic Research. 3

Görg, H., Henry, M., and Strobl, E. (2008). Grant Support and Exporting Activity. *The Review of Economics and Statistics*, 90(1):168–174. 69

Görg, H. and Strobl, E. (2007). The Effect of R&D Subsidies on Private R&D. *Economica*, 74(294):215–234. 17

Gornall, W. and Strebulaev, I. A. (2015). The Economic Impact of Venture Capital: Evidence from Public Companies. 18

Gourieroux, C., Monfort, A., and Trognon, A. (1984). Pseudo Maximum Likelihood Methods: Theory. *Econometrica: Journal of the Econometric Society*, pages 681–700. 81

Greene, W. (2011). Fixed Effects Vector Decomposition: A Magical Solution to the Problem of Time-invariant Variables in Fixed Effects Models? *Political Analysis*, 19(2):135–146. 39

Griffith, R., Harisson, R., et al. (2004). The Link Between Product Market Reform and Macro-economic Performance. Technical report, Directorate General Economic and Financial Affairs (DG ECFIN), European Commission. 33, 34, 45

Griffith, R., Harrison, R., and Simpson, H. (2010). Product Market Reform and Innovation in the EU. *Scandinavian Journal of Economics*, 112(2):389–415. 28, 31, 40

Griffith, R., Redding, S., and Van Reenen, J. (2003). R&D and Absorptive Capacity: Theory and Empirical Evidence. *Scandinavian Journal of Economics*, 105(1):99–118. 12

Griliches, Z. (1958). Research Costs and Social Returns: Hybrid Corn and Related Innovations. *Journal of Political Economy*, 66(5):419–431. 12

Griliches, Z. (1990). Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature*, 28(4):1661–1707. 32, 96

Griliches, Z. (1992). The Search for R&D Spillovers. *The Scandinavian Journal of Economics*, pages S29–S47. 189

Grossman, G. M. and Helpman, E. (1991). Quality Ladders in the Theory of Growth. *The Review of Economic Studies*, 58(1):43–61. 8, 14, 16, 27

Guceri, I. and Liu, L. (2019). Effectiveness of Fiscal Incentives for R&D: Quasi-experimental Evidence. *American Economic Journal: Economic Policy*, 11(1):266–91. 13, 17, 66, 69, 81, 82, 91, 96, 97

Guo, D., Guo, Y., and Jiang, K. (2016). Government-subsidized R&D and Firm Innovation: Evidence from China. *Research Policy*, 45(6):1129–1144. 69, 70

Hall, B. and Harhoff, D. (2012). Recent Research on the Economics of Patents. NBER Working Papers 17773, National Bureau of Economic Research, Inc. 33

Hall, B. H. (2002). The Financing of Research and Development. *Oxford Review of Economic Policy*, 18(1):35–51. 14

Hall, B. H., Griliches, Z., and Hausman, J. A. (1986). Patents and R and D: Is There a Lag? *International Economic Review*, 27(2):265–283. 89

Hall, B. H., Mairesse, J., and Mohnen, P. (2010). Measuring the Returns to R&D. In *Handbook of the Economics of Innovation*, volume 2, pages 1033–1082. Elsevier. 10, 13, 14, 16, 32, 67, 68, 91, 93

Hall, B. H., Moncada-Paternò-Castello, P., Montresor, S., and Vezzani, A. (2016). Financing Constraints, R&D Investments and Innovative Performances: New Empirical Evidence at the Firm Level for Europe. 13

Hallen, B. L., Bingham, C. B., and Cohen, S. (2014). Do Accelerators Accelerate? A Study of Venture Accelerators as a Path to Success? In *Academy of management proceedings*, volume 2014, page 12955. Academy of Management Briarcliff Manor, NY 10510. 114

Hausman, J. A. (1997). Valuation of New Goods Under Perfect and Imperfect Competition. In *The Economics of New Goods*, pages 207–248. University of Chicago Press. 43

Hellmann, T. and Puri, M. (2000). The Interaction Between Product Market and Financing Strategy: The Role of Venture Capital. *The Review of Financial Studies*, 13(4):959–984. 18

Hildebrand, T., Puri, M., and Rocholl, J. (2017). Adverse Incentives in Crowdfunding. *Management Science*, 63(3):587–608. 114

Himmelberg, C. P. and Petersen, B. C. (1994). R&D and Internal Finance: A Panel Study of Small Firms in High-tech Industries. *The Review of Economics and Statistics*, pages 38–51. 68

Hochberg, Y., Serrano, C. J., and Ziedonis, R. H. (2018). Patent Collateral, Investor Commitment, and the Market for Venture Lending. *Journal of Financial Economics*. 68

Hottenrott, H. and Demeulemeester, S. (2017). R&D Subsidies and Firms' Cost of Debt. 68

Hottenrott, H., Lins, E., and Lutz, E. (2017). Public Subsidies and New Ventures' Use of Bank Loans. *Economics of Innovation and New Technology*, pages 1–23. 70

Howell, S. (2018). Learning from Feedback: Evidence from New Ventures. *Available at SSRN 3047811*. 19, 154

Howell, S. T. (2017). Financing Innovation: Evidence from R&D Grants. *American Economic Review*, 107(4):1136–64. 13, 16, 17, 21, 64, 66, 69, 70, 74, 81, 84, 94, 95, 97, 186

Howell, S. T. (2019). Reducing Information Frictions in Venture Capital: The Role of New Venture Competitions. *Journal of Financial Economics*. 14, 19, 118, 119, 123, 125, 129, 135, 142, 151, 154, 156

Howell, S. T. and Nanda, R. (2019). Networking Frictions in Venture Capital, and the Gender Gap in Entrepreneurship. Technical report, National Bureau of Economic Research. 151

Hsiao, C. (2003). Analysis of Panel Data (Vol. 34). *Econometric Society Monographs*. 38

Hünermund, P. and Czarnitzki, D. (2019). Estimating the Causal Effect of R&D Subsidies in a Pan-European Program. *Research Policy*, 48(1):115–124. 17, 66, 69, 86

Imbens, G. (2019). Potential Outcome and Directed Acyclic Graph Approaches to Causality: Relevance for Empirical Practice in Economics. Technical report, National Bureau of Economic Research. 48

Imbens, G. and Angrist, J. (1994). Identification and Estimation of Local Average Treatment Effects. *Econometrica*, 62(2):467–475. 138

Impullitti, G. and Licandro, O. (2018). Trade, Firm Selection and Innovation: The Competition Channel. *The Economic Journal*, 128(608):189–229. 31

Jaffe, A. (1986). Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value. *American Economic Review*, 76(5):984–1001. 12

Jaffe, A. B. (2002). Building Programme Evaluation into the Design of Public Research-support Programmes. *Oxford Review of Economic Policy*, 18(1):22–34. 69

Kaplan, S. N. and Lerner, J. (2010). It Ain't Broke: The Past, Present, and Future of Venture Capital. *Journal of Applied Corporate Finance*, 22(2):36–47. 18, 114

Kaplan, S. N., Sensoy, B. A., and Strömberg, P. (2009). Should Investors Bet on the Jockey or the Horse? Evidence from the Evolution of Firms from Early Business Plans to Public Companies. *The Journal of Finance*, 64(1):75–115. 118

Kaplan, S. N. and Stromberg, P. (2001). Venture Capitals as Principals: Contracting, Screening, and Monitoring. *American Economic Review*, 91(2):426–430. 18, 132

Keller, W. (2004). International Technology Diffusion. *Journal of Economic Literature*, 42(3):752–782. 12

Kelley, H. H. (1973). The Processes of Causal Attribution. *American psychologist*, 28(2):107. 134

Kerr, W. R. and Nanda, R. (2015). Financing Innovation. *Annual Review of Financial Economics*, 7:445–462. 13

Kerr, W. R., Nanda, R., and Rhodes-Kropf, M. (2014). Entrepreneurship as Experimentation. *Journal of Economic Perspectives*, 28(3):25–48. 118, 123, 124, 153

Klette, T. J. and Kortum, S. (2004). Innovating Firms and Aggregate Innovation. *Journal of Political Economy*, 112(5):986–1018. 9

Kling, J. R. (2006). Incarceration Length, Employment, and Earnings. *American Economic Review*, 96(3):863–876. 137, 139

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological Innovation, Resource Allocation, and Growth. *The Quarterly Journal of Economics*, 132(2):665–712. 96

Lach, S. (2002). Do R&D Subsidies Stimulate or Displace Private R&D? Evidence from Israel. *The Journal of Industrial Economics*, 50(4):369–390. 17, 69, 91

Lanahan, L. and Armanios, D. (2018). Does More Certification Always Benefit a Venture? *Organization Science*, 29(5):931–947. 68

Le, T. and Jaffe, A. B. (2017). The Impact of R&D Subsidy on Innovation: Evidence from New Zealand Firms. *Economics of Innovation and New Technology*, 26(5):429–452. 69

Leatherbee, M. and Katila, R. (2017). Stay the Course or Pivot? Antecedents of Cognitive Refinements of Business Models in Young Firms. In *Academy of Management Proceedings*. 19

Leland, H. E. and Pyle, D. H. (1977). Informational Asymmetries, Financial Structure, and Financial Intermediation. *The Journal of Finance*, 32(2):371–387. 14

Lentz, R. and Mortensen, D. T. (2008). An Empirical Model of Growth through Product Innovation. *Econometrica*, 76(6):1317–1373. 9

Lentz, R. and Mortensen, D. T. (2016). Optimal Growth through Product Innovation. *Review of Economic Dynamics*, 19:4–19. 9

Lerner, J. (2000). The Government as Venture Capitalist: The Long-run Impact of the SBIR Program. *The Journal of Private Equity*, pages 55–78. 21, 64, 66, 67, 68, 69, 93, 94

Lerner, J. (2013). *Boulevard of Broken Dreams: Why Public Efforts to Boost Entrepreneurship and Venture Capital Have Failed–and What to Do About it*. Princeton University Press. 18

Levine, R. and Renelt, D. (1992). A Sensitivity Analysis of Cross-country Growth Regressions. *The American Economic Review*, pages 942–963. 45

Li, L. I., Tadelis, S., and Zhou, X. (2016). Buying Reputation as a Signal of Quality: Evidence from an Online Marketplace. Technical report, National Bureau of Economic Research. 119

Lopez, J. and Mairesse, J. (2018). Impacts du CIR sur les Principaux Indicateurs d'Innovation des Enquêtes CIS et la Productivité des Entreprises. Technical report, France Stratégie. 6

Luca, M. (2016). Reviews, Reputation, and Revenue: The Case of Yelp. com. *Com (March 15, 2016). Harvard Business School NOM Unit Working Paper*, (12-016). 119

Lucas Jr, R. E. (1988). On the Mechanics of Economic Development. *Journal of Monetary Economics*, 22(1):3–42. 8

Lucking-Reiley, D., Bryan, D., Prasad, N., and Reeves, D. (2007). Pennies from eBay: The Determinants of Price in Online Auctions. *The Journal of Industrial Economics*, 55(2):223–233. 119

Lundvall, B.-Å. (2010). *National Systems of Innovation: Toward a Theory of Innovation and Interactive Learning*, volume 2. Anthem press. 10

Mairesse, J. and Mohnen, P. (2010). Using Innovations Surveys for Econometric Analysis. NBER Working Papers 15857, National Bureau of Economic Research, Inc. 32

Mann, W. (2018). Creditor Rights and Innovation: Evidence from Patent Collateral. *Journal of Financial Economics*. 68

Mansfield, E. (1986). Patents and Innovation: An Empirical Study. *Management Science*, 32(2):173–181. 33

Mansfield, E., Rapoport, J., Romeo, A., Wagner, S., and Beardsley, G. (1977). Social and Private Rates of Return from Industrial Innovations. *The Quarterly Journal of Economics*, 91(2):221–240. 67

Mansfield, E., Schwartz, M., and Wagner, S. (1981). Imitation Costs and Patents: An Empirical Study. *The Economic Journal*, 91(364):907–918. 12

Marino, M., Lhuillery, S., Parrotta, P., and Sala, D. (2016). Additionality or Crowding-out? An Overall Evaluation of Public R&D Subsidy on Private R&D Expenditure. *Research Policy*, 45(9):1715–1730. 17

Mastrobuoni, G. and Pinotti, P. (2015). Legal Status and the Criminal Activity of Immigrants. *American Economic Journal: Applied Economics*, 7(2):175–206. 78

Mazars (2019). *Les Startups Early Stage en France : Pratiques et Perspectives*. 130

McKenzie, D. (2017). Identifying and Spurring High-Growth Entrepreneurship: Experimental Evidence from a Business Plan Competition. *American Economic Review*, 107(8):2278–2307. 114, 118, 154

McKenzie, D. and Sansone, D. (2019). Predicting Entrepreneurial Success is Hard: Evidence from a Business Plan Competition in Nigeria. *Journal of Development Economics*, 141:102369. 118, 120, 135, 157

Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica*, 71(6):1695–1725. 16, 31

Melitz, M. J. and Ottaviano, G. I. (2005). Market Size, Trade, and Productivity. Working Paper 11393, National Bureau of Economic Research. 31

Meuleman, M. and De Maeseneire, W. (2012). Do R&D Subsidies Affect SMEs' Access to External Financing? *Research Policy*, 41(3):580–591. 66, 69, 94, 95

Modigliani, F. and Miller, M. H. (1958). The Cost of Capital, Corporation Finance and the Theory of Investment. *The American Economic Review*, 48(3):261–297. 13

Mollick, E. and Nanda, R. (2016). Wisdom or Madness? Comparing Crowds with Expert Evaluation in Funding the Arts. *Management Science*, 62(6):1533–1553. 19, 114, 122

Mollick, E. R. (2013). Swept Away by the Crowd? Crowdfunding, Venture Capital, and the Selection of Entrepreneurs. *Venture Capital, and the Selection of Entrepreneurs (March 25, 2013)*. 19, 114

Moretti, E. and Wilson, D. J. (2014). State Incentives for Innovation, Star Scientists and Jobs: Evidence from Biotech. *Journal of Urban Economics*, 79:20–38. 69

Moser, P. (2005). How do Patent Laws Influence Innovation? Evidence from Nineteenth-century World's Fairs. *American Economic Review*, 95(4):1214–1236. 33

Myers, S. C. and Majluf, N. S. (1984). Corporate Financing and Investment Decisions When Firms Have Information that Investors Do Not Have. *Journal of Financial Economics*, 13(2):187–221. 14, 67

Negassi, S., Lhuillery, S., Sattin, J.-F., Hung, T.-Y., and Pratlong, F. (2019). Does the Relationship between Innovation and Competition Vary Across Industries? Comparison of Public and Private Research Enterprises. *Economics of Innovation and New Technology*, 28(5):465–482. 27, 30

Nelson, R. R. (1959). The Simple Economics of Basic Scientific Research. *Journal of Political Economy*, 67(3):297–306. 9, 10, 16, 67

Nelson, R. R. (1993). *National Innovation Systems: A Comparative Analysis*. Oxford University Press on Demand. 10

Neumark, D. and Simpson, H. (2015). Place-based Policies. In *Handbook of Regional and Urban Economics*, volume 5, pages 1197–1287. Elsevier. 64, 189

Nickell, S. J. (1996). Competition and Corporate Performance. *Journal of Political Economy*, 104(4):724–746. 28, 30

Nicoletti, G. and Scarpetta, S. (2003). Regulation, Productivity and Growth: OECD Evidence. *Economic Policy*, 18(36):9–72. 28, 30

OECD (2019). OECD Compendium of Productivity Indicators 2019. Technical report, OECD. 2, 130

Ohrn, E. (2018). The Effect of Corporate Taxation on Investment and Financial Policy: Evidence from the DPAD. *American Economic Journal: Economic Policy*, 10(2):272–301. 66, 81, 87, 97

Olea, J. L. M. and Pflueger, C. (2013). A Robust Test for Weak Instruments. *Journal of Business & Economic Statistics*, 31(3):358–369. 140

Oster, E. (2019). Unobservable Selection and Coefficient Stability: Theory and Evidence. *Journal of Business & Economic Statistics*, 37(2):187–204. 117, 148, 149, 175

Pearl, J. (1995). Causal Diagrams for Empirical Research. *Biometrika*, 82(4):669–688. 28, 47

Pearl, J. (2009). *Causality: Models, Reasoning and Inference*. Cambridge University Press, New York, NY, USA, 2nd edition. 46, 48

Perla, J., Tonetti, C., and Waugh, M. E. (2015). Equilibrium Technology Diffusion, Trade, and Growth. Technical report, National Bureau of Economic Research. 31

Phelps, E. S. (1972). The Statistical Theory of Racism and Sexism. *The American Economic Review*, 62(4):659–661. 115, 130, 134

Plümper, T. and Troeger, V. E. (2007). Efficient Estimation of Time-Invariant and Rarely Changing Variables in Finite Sample Panel Analyses with Unit Fixed Effects. *Political Analysis*, 15(02):124–139. 38

Rao, N. (2016). Do Tax Credits Stimulate R&D Spending? The Effect of the R&D Tax Credit in its First Decade. *Journal of Public Economics*, 140:1 – 12. 66, 96

Reinganum, J. F. (1983). Uncertain Innovation and the Persistence of Monopoly. *The American Economic Review*, 73(4):741–748. 27

Rivest, L.-P. (1994). Statistical Properties of Winsorized Means for Skewed Distributions. *Biometrika*, 81(2):373–383. 126

Romer, P. M. (1986). Increasing Returns and Long-run Growth. *Journal of Political Economy*, 94(5):1002–1037. 8

Romer, P. M. (1990). Endogenous Technological Change. *Journal of Political Economy*, 98(5, Part 2):S71–S102. 8, 27

Ross, L., Greene, D., and House, P. (1977). The “false consensus effect”: An Egocentric Bias in Social Perception and Attribution Processes. *Journal of Experimental Social Psychology*, 13(3):279–301. 134

Rubin, D. B. (1974). Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies. *Journal of Educational Psychology*, 66(5):688. 78

Santoleri, P., Mina, A., Di Minin, A., Martelli, I., et al. (2020). The Causal Effects of R&D Grants: Evidence from a Regression Discontinuity. Technical report, Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced. 74, 186

Schumpeter, J. (1911). The Theory of Economic Development. Harvard Economic Studies. Vol. XLVI. 8

Schumpeter, J. (1942). Creative Destruction. *Capitalism, socialism and democracy*, 825:82–85. 18

Schumpeter, J. A. (1934). The Theory of Economic Development (translation of second German edition by Redvers Opie). *Cambridge, MA, Harvard University*. 15, 16, 27

Scott, E. L., Shu, P., and Lubynsky, R. M. (2020). Entrepreneurial Uncertainty and Expert Evaluation: An Empirical Analysis. *Management Science*, 66(3):1278–1299. 118

Smith, A. (1776). The Wealth of Nations. *New York: The Modern Library*. 8, 18

Söderblom, A., Samuelsson, M., Wiklund, J., and Sandberg, R. (2015). Inside the Black Box of Outcome Additionality: Effects of Early-stage Government Subsidies on Resource Accumulation and New Venture Performance. *Research Policy*, 44(8):1501–1512. 17

Solow, R. M. (1956). A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics*, 70(1):65–94. 8

Spence, M. (1973). Job Market Signaling. *The Quarterly Journal of Economics*, 87(3):355–374. 93

Spirtes, P., Glymour, C., N., S., and Richard (2000). *Causation, Prediction, and Search*. Mit Press: Cambridge. 46

Stiglitz, J. E. and Weiss, A. (1981). Credit Rationing in Markets with Imperfect Information. *The American Economic Review*, 71(3):393–410. 67

Stock, J. H. and Yogo, M. (2005). Testing for Weak Instruments in Linear IV Regression. *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, page 80. 43, 140

Swan, T. W. (1956). Economic Growth and Capital Accumulation. *Economic Record*, 32(2):334–361. 8

Syverson, C. (2017). Challenges to Mismeasurement Explanations for the US Productivity Slowdown. *Journal of Economic Perspectives*, 31(2):165–86. 3

Takalo, T. and Tanayama, T. (2010). Adverse Selection and Financing of Innovation: Is there a Need for R&D Subsidies? *The Journal of Technology Transfer*, 35(1):16–41. 70

Teece, D. J. (1996). Firm Organization, Industrial Structure, and Technological Innovation. *Journal of Economic Behavior & Organization*, 31(2):193–224. 34

Teece, D. J. (2010). Technological Innovation and the Theory of the Firm: The Role of Enterprise-level Knowledge, Complementarities, and (Dynamic) Capabilities. In *Handbook of the Economics of Innovation*, volume 1, pages 679–730. Elsevier. 10

Tian, X. and Wang, T. Y. (2014). Tolerance for Failure and Corporate Innovation. *The Review of Financial Studies*, 27(1):211–255. 118, 130

Tingvall, P. G. and Poldahl, A. (2006). Is there Really an Inverted U-shaped Relation between Competition and R&D? *Economics of Innovation and New Technology*, 15(2):101–118. 27, 30

Turner, L. and Boulhol, H. (2008). Recent Trends and Structural Breaks in US and EU15 Labour Productivity Growth. 1

Van Ark, B., O'Mahoney, M., and Timmer, M. P. (2008). The Productivity Gap between Europe and the United States: Trends and Causes. *Journal of Economic Perspectives*, 22(1):25–44. 1

Wallsten, S. J. (2000). The Effects of Government-industry R&D Programs on Private R&D: The Case of the Small Business Innovation Research Program. *The RAND Journal of Economics*, pages 82–100. 17, 68, 69

Wang, Y., Li, J., and Furman, J. L. (2017). Firm Performance and State Innovation Funding: Evidence from China's Innofund Program. *Research Policy*, 46(6):1142–1161. 69

Westmore, B. (2013). R&D, Patenting and Growth. 29, 45

Williamson, O. E. (1988). Corporate Finance and Corporate Governance. *The Journal of Finance*, 43(3):567–591. 13

Wölfl, A., Wanner, I., Kozluk, T. J., and Nicoletti, G. (2009). Ten Years of Product Market Reform in OECD Countries-insights from a Revised PMR Indicator. 29

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. MIT press. 38, 136

Xavier, S.-i.-M. et al. (1997). I Just Ran Two Million Regressions. *American Economic Review*, 87(2):178–83. 45

Xu, R. and Gong, K. (2017). *Does Import Competition Induce R&D Reallocation? Evidence from the US*. International Monetary Fund. 16

Yagan, D. (2015). Capital Tax Reform and the Real Economy: The effects of the 2003 Dividend Tax Cut. *American Economic Review*, 105(12):3531–63. 66, 81

Yu, S. (2020). How Do Accelerators Impact the Performance of High-technology Ventures? *Management Science*, 66(2):530–552. 19

Zhao, B. and Ziedonis, R. (2020). State Governments as Financiers of Technology Startups: Evidence from Michigan's R&D Loan Program. *Research Policy*, 49(4):103926. 17, 69

Zimmermann, F. (2020). The Dynamics of Motivated Beliefs. *American Economic Review*, 110(2):337–61. 147

Zúñiga-Vicente, J. Á., Alonso-Borrego, C., Forcadell, F. J., and Galán, J. I. (2014). Assessing the Effect of Public Subsidies on Firm R&D Investment: A Survey. *Journal of Economic Surveys*, 28(1):36–67. 17, 68

Zwick, E. and Mahon, J. (2017). Tax Policy and Heterogeneous Investment Behavior. *American Economic Review*, 107(1):217–48. 66, 81, 90, 97

List of Tables

List of Figures

Abstract / Résumé

This thesis studies different aspects of the factors that directly or indirectly impact innovative activities both at the macroeconomic and microeconomic levels. In a context where policymakers and firms consider innovation as a strategic asset for productivity growth, this thesis aims at contributing to the literature on the determinants of innovation and related market failures relying on primarily empirical contributions. The first chapter considers the impact of competition and trade openness on innovation. Country innovation intensity positively responds to less stringent regulation, but only domestic product-market reform is directly related to innovation. The second chapter evaluates a European program that supports SME's innovation. R&D grants positively impact patenting, but this effect is stronger for more financially constrained firms by a certification mechanism on the quality of firms. Finally, the third chapter considers the role of information frictions among a crowd-rating framework, on ventures' subsequent success. This chapter uses a novel sample of French ventures at both the idea and seed stage. Taken together, this thesis explores three different instruments that aim to spur innovation intensity, either in terms of R&D, patents, financing, and venture success outcomes.

Keywords: Innovation, R&D, Competition, Financing Constraints

⋆⋆⋆⋆⋆

Cette thèse étudie différents aspects concernant les facteurs qui ont un impact direct ou indirect sur les activités innovantes aux niveaux macroéconomique et microéconomique. Dans un contexte où les décideurs politiques et les entreprises considèrent l'innovation comme un atout stratégique pour la croissance de la productivité, cette thèse vise à contribuer à la littérature sur les déterminants de l'innovation et les défaillances du marché associées en s'appuyant principalement sur des contributions empiriques. Le premier chapitre examine l'impact de la concurrence et de l'ouverture commerciale sur l'innovation. L'intensité d'innovation des pays répond positivement à une réglementation moins stricte, mais que seule la réforme intérieure du marché des produits est directement liée à l'innovation. Le deuxième chapitre évalue un programme européen qui soutient l'innovation des PME. Les subventions de R&D ont un impact positif sur les brevets, mais cet effet est plus fort pour les entreprises plus contraintes financièrement par un mécanisme de certification sur la qualité des entreprises. Enfin, le troisième chapitre examine le rôle des frictions informationnelles dans un cadre de notation par la foule, sur le succès ultérieur des startups. Ce chapitre utilise un nouvel échantillon d'entreprises françaises à la fois au stade de l'idée et de la phase de démarrage. Dans l'ensemble, cette thèse explore trois instruments différents qui visent à stimuler l'intensité de l'innovation, que ce soit en termes de R&D, de brevets, de financement et de facteurs de succès des entreprises.

Mots-Clés : Innovation, R&D, Concurrence, Contraintes de Financement

216