Impact of health shocks on personality traits, economic preferences, and risky behaviors

Antoine Marsaudon

UNIVERSITÉ PARIS 1 PANTHÉON SORBONNE

PARIS SCHOOL OF ECONOMICS

Laboratoire de rattachement: Paris-Jourdan Sciences Economiques

THÈSE

pour l'obtention du titre de Docteur en Sciences Économiques

Présentée et soutenue publiquement le 1^er^ juillet 2019 par

Antoine MARSAUDON

Impact of Health Shocks on Personality Traits, Economic Preferences, and Risky Behaviors

Préparée sous la direction de Lise ROCHAIX et Mattéo M. GALIZZI

Composition du jury :

Rapporteurs	
Andrew JONES	Pr., Université de York
Marjon VAN DER POL	Pr., Université d'Aberdeen
President	
Nicolas JACQUEMET	Pr., Université Paris 1 Panthéon-Sorbonne et PSE
Examinateur	
Andrew CLARK	Pr., CNRS et École Normale Supérieure
Directeurs	
Lise ROCHAIX	Pr., Université Paris 1 Panthéon-Sorbonne
Mattéo M. GALIZZI	Pr., London School of Economics

L'université Paris 1 Panthéon-Sorbonne n'entend donner aucune approbation, ni improbation aux opinions émises dans cette thèse : elles doivent être considérées comme propres à leur auteur.

À mes parents.

REMERCIEMENTS

Après quatre années de travail, l'achèvement de cette thèse représente une étape importante. Elle est non seulement l'aboutissement d'un chemin - non linéaire - d'un apprentissage professionnel, mais surtout personnel. Je tiens à remercier tout ceux qui auront concouru à sa réalisation.

⋆ ⋆ ⋆ ⋆ ⋆

Mes premiers remerciements s'adressent à ma directrice de thèse, Lise Rochaix. Depuis mes premières statistiques descriptives d'assistant de recherche jusqu'au point final de cette thèse, Lise aura été d'un soutien indispensable. La singularité et le discernement de son encadrement, alliant exigence et bienveillance, m'auront été essentiels. Je n'ai jamais osé compter le nombre de relectures, de commentaires et de conseils donnés en quatre ans, mais je sais mesurer combien ils auront comblé mes imprécisions et mes doutes. Ce ne sont là que quelques mots lui témoignant ma très profonde gratitude.

Je remercie Mattéo M. Galizzi, co-directeur de cette thèse, pour m'avoir accueilli et reçu comme un pair pendant mon échange à Londres. J'espère m'être suffisamment imprégné de sa modestie et de son humilité.

Je tiens à remercier grandement Andrew Jones et Marjon van der Pol qui me font l'honneur d'être les rapporteurs de cette thèse. La précision de leurs retours, en conférence et dans les rapports de pré-soutenance, aura donné plus de finesse et de justesse à mes travaux.

Un grand merci également à Andrew Clark pour avoir fait partie de mon comité de thèse et donc d'avoir suivi l'acheminement progressif de l'ensemble des papiers en chapitres. Nos discussions et ses compétences en économétrie auront été bénéfiques à bien des égards.

Mes remerciements vont également à Nicolas Jacquemet pour avoir accepté le rôle de président du jury.

Merci aux nombreux chercheurs qui ont commenté, annoté et lu les travaux de cette thèse pendant les divers séminaires et conférences. Merci donc à Yves Arrighi, Lisa Chauvet, Brigitte Dormont, Hélène Hubert, Fabrice Le Lec, Célia Lemaire, Olivier L'Haridon, Jean-Pierre Messe, Pierre Morin, Catherine Polak, Xavier Rousset, Alexandre Sauquet, Sulin

Sardoschau, Nicolas Sirven, Carole Treibich, Brendan Vannier et Rémi Yin.

Je remercie chaleureusement les économistes (de la santé et les autres) qui ont eu la gentillesse de m'entourer dès mes débuts : Thomas Barnay, Jean Beuve, Christine Le Clainche, Pauline Chauvin, Izabela Jelovac, Florence Jusot, Christine Meyer, Antoine Nebout, Silvana Robone, Josselin Thuilliez, Sandy Tubeuf et Jean-Christophe Vergnaud. Un grand merci également à mes ainées : Victoire Girard, Léontine Goldzahl, Marlène Guillon, Sara Machado et Marianne Tenand pour leurs conseils.

En amont de cette thèse, il y a aussi tous ceux qui m'ont transmis l'envie de comprendre. Je souhaite témoigner l'importance qu'ont eu Elisabeth Cudeville et Stéphane Gauthier pour inspirer et motiver ce projet. Je suivais leurs cours autant pour leurs contenus que pour les écouter en parler.

⋆ ⋆ ⋆ ⋆ ⋆

J'aimerais maintenant passer à ceux sans qui le quotidien de ces quatre dernières années aurait été bien moins agréable.

Ce quotidien aura été de retrouver tous ceux qui sont, un jour, passés par l'open-space d'Hospinnomics : Eliana, Ivy, Maria, Ivan, Rolando, Alek, Léa, Laurie, Olivier, Estelle, Camille, Laurène, Candice, Véronique, Daniel, Jean, Marc-Antoine, Noémie, Quitterie, Audrey, Réka, Rita et Bastien. J'ai partagé avec vous plus que des régressions et des pannes de Wi-fi. Merci d'avoir été attentif, compréhensif et valorisant. Vous resterez associé à mes "années de thèse" que je ne risque pas d'oublier. Merci également à Jean-Claude pour ses attentions quotidiennes et son regard bienveillant.

Je tiens à remercier tout particulièrement Thomas, Natacha et Setti. Thomas avec qui on a presque réussi à terminer nos thèses ensembles. Merci pour toutes ces places réservées en amphi, à la BSB, à la BSG, ou à la BnF. Merci pour les explications en économétrie et merci d'avance pour celles à venir. Merci à Natacha pour avoir m'avoir accompagné dans toutes les étapes de ces dernières années. Sa résilience m'inspire et son amitié m'est essentielle. Merci à Setti pour avoir donné du sens à tous ces jours, week-ends et nocturnes de travail. Pouvoir compter sur sa présence et son soutien fut l'une de mes rares certitudes. Cette thèse lui doit beaucoup, je lui dois encore plus.

Merci à Vincent et à François d'être les meilleurs frères. Vous avoir à mes côtés me donne bien plus de force que je n'en aurai jamais. Merci à Marie-Camille pour son écoute et son soutien. Merci à Hortense qui vient de nous rejoindre.

Enfin, un immense merci à mes parents qui n'ont cessé de m'encourager et de m'épauler pendant toutes ces années. Votre amour, vos inquiétudes et votre soutien me touchent et me portent depuis toujours. Merci pour vos concessions qui m'ont permis d'avoir tous les choix. Je mesure toute la chance que j'ai de vous avoir. Ce travail vous est dédié.

⋆ ⋆ ⋆ ⋆ ⋆

Antoine

Table of contents

Funding information / Financements des recherches

Different institutions have funded this PhD dissertation.

The Hospinnomics Research Chair (PSE-Ecole d'Économie de Paris, Assistance Publique des Hôpitaux de Paris –AP-HP)[1] has funded the first part of the thesis (from November, 2015 to March, 2017). The French Institute for Public Health Research (IReSP)[2] financed the second part of this thesis (from February, 2017 to October, 2018) through the 2015 call launched by this institution.

Chapter 2 results have been funded by an international mobility grant received from Paris 1 Panthéon-Sorbonne University in June 2017, for a visiting stay at the London School of Economics. The last year of this PhD dissertation was apartly funded by Paris 1 Panthéon-Sorbonne University (part-time teaching) with additional funding by Hospinnomics (from November, 2018 to October, 2019).

⋆ ⋆ ⋆ ⋆ ⋆

[1] More details on Hospinnomics' governance and funding sources can be found on the website: https://www.hospinnomics.eu/projet-scientifique/.

[2] To know more about IReSP, the reader can refer to: http://www.iresp.net.

Cette thèse a bénéficié du soutien de plusieurs isntitutions et de différentes sources de financement.

Elle a d'abord été financée par la Chaire de recherche Hospinnomics (PSE-Ecole d'Économie de Paris, Assistance Publique des Hôpitaux de Paris –AP-HP) puis par l'Institut de Recherche en Santé publique (IReSP). Ces deux financements se sont succédés, le premier a été alloué pendant la première partie de la thèse (novembre 2015-mars 2017) et le second pendant la deuxième partie (février 2017-octobre 2018). Le financement provenant de l'IReSP a été obtenu dans le cadre de l'appel à projet portant sur la "recherche sur les services de santé et cancer" lancé par cet institut en 2015.

Les analyses menées dans le chapitre 2 ont été financées par une bourse de mobilité internationale reçue de l'Université Paris 1 Panthéon-Sorbonne en juin 2017. Ce financement à permis un séjour à la London School of Economics. La dernière année de thèse a été financée par l'Université Paris 1 Panthéon-Sorbonne (demi-ATER) auquel un financement supplémentaire a été apporté par la Chaire Hospinnomics. Ces deux financements ont été obtenus conjointement pour une durée de 1 an (novembre 2018-octobre 2019).

⋆ ⋆ ⋆ ⋆ ⋆

Reading guide / Guide de lecture

This PhD dissertation is written in English to facilitate its dissemination and to foster discussions with non-French readers. For French readers, a summary in French is proposed at the beginning of the manuscript.

The General Introduction contains five sections and provides the contributions of the thesis. It aims at providing a comprehensive overview of previous and current results of the economics literature. It also delivers the motivations of the research questions developed throughout the PhD. This thesis is based on four empirical papers constituting four chapters. Each chapter was written as to be a standalone work. Therefore, some similar explanations or references can be found in different parts. For the reader to have an overview of the chapter, an abstract comes before the introduction of each paper. The thesis ends with a General Conclusion discussing the main results and highlighting avenues for future research.

An appendix containing additional tables and figures along with all references are provided at the end of this manuscript.

⋆ ⋆ ⋆ ⋆ ⋆

Cette thèse a été écrite en anglais pour en faciliter sa dissémination auprès d'un public non francophone. Un résumé en français est toutefois proposé au début du manuscrit.

La thèse comporte une introduction générale, quatre chapitres et une conclusion générale. L'introduction générale a été écrite dans l'objectif de proposer une vue d'ensemble des résultats de la littérature économique, préalable nécessaire pour poser les questions qui seront développées dans les différents chapitres. La thèse se structure autour de quatre articles empiriques constituant quatre chapitres. Chaque partie a été rédigée de manière à pouvoir être lu de manière indépendante. De ce fait, des explications et des références bibliographiques se retrouvent dans plusieurs chapitres. Pour une lecture rapide, le lecteur peut se référer au résumé proposé avant chaque chapitre. Cette thèse se termine par une conclusion générale rappelant les principaux résultats et proposant des pistes de prolongement.

Une annexe contenant les tableaux et les graphiques supplémentaires, c'est-à-dire non présent dans les parties ci-dessous, est disponible à la fin de ce manuscrit.

⋆ ⋆ ⋆ ⋆ ⋆

Summary in French / Présentation de la thèsen en français

Sommaire

1. Définition des traits de personnalité et des préférences économiques

Les modes de vie ont un impact fort sur la santé puisqu'ils augmentent le risque de développer une maladie non-transmissible (MNT) comme une maladie cardio-vasculaire, un cancer ou du diabète. Aujourd'hui, les MNT sont un problème mondial de santé publique. En 2018, l'Organisation Mondiale de la Santé (OMS) a estimé que plus de 70 % des décès dans le monde sont causés par ces maladies. Les pathologies cardio-vasculaires sont responsables du plus grand nombre de ces décès : 17,9 millions, suivis par les cancers (9 millions) et le diabète (1,6 million). Les maladies liées aux modes de vie ont en commun des facteurs de risque similaires associés à l'exposition prolongée à certains comportements : tabagisme, consommation excessive d'alcool, sédentarité ou un régime alimentaire déséquilibré (WHO (2018)). Pris séparément, ces comportements ont également de lourdes conséquences puisque le tabagisme tue plus de 7 millions de personnes chaque année dans le monde, et sera responsable d'un décès toutes les trois secondes en 2030. L'excès d'alcool, quant à lui, est responsable chaque année de 3 millions de décès dans le monde, soit d'1 mort sur 20 ; et 2,8 millions de personnes décèdent chaque année de leur surpoids[3] ou de leur obésité[4].

Les déterminants de ces comportements de santé sont complexes et nombreux : ils dépendent notamment du revenu, du niveau d'études, du lieu de vie, de l'offre de soin, du sexe, du capital social ou encore de la culture (e.g. Lundborg and Andersson (2008); Currie (2009); Cutler and Lleras-Muney (2010); Conti et al. (2010); Schünemann et al. (2017)).

En plus de ces caractéristiques socio-économiques et socio-démographiques, les comportements de santé peuvent aussi être expliqués par des caractéristiques plus personnelles, comme les traits de personnalité (e.g. l'ouverture d'esprit, la diligence, l'estime de soi, la perception du contrôle) ou les préférences économiques (i.e. les préférences sociales et les préférences vis-à-vis du risque et du temps).

[3]Le surpoids est défini par un IMC supérieur à 25.
[4]L'obésité est définie par un IMC supérieur à 30.

1.1. Les traits de personnalité...

Au cours des dernières décennies l'indicateur dimensionnel en cinq facteurs ("Big-Five") a pris une place prépondérante dans la description de la personnalité. Introduit par Costa and McCrae (1992a); Costa and McCrae (1992b) et Goldberg (1992), il semble faire l'objet d'un consensus sur la taxonomie générale des traits de personnalité. Cet indicateur ne classe pas les personnes en cinq catégories, mais les évalue sur chacun des cinq facteurs suivants : le niveau de névrose, l'extraversion, l'amabilité, l'ouverture d'esprit et sur le fait d'être consciencieux.

Un autre indicateur utilisé par la littérature en psychologie de la personnalité, et introduit par la théorie de l'apprentissage sociale, est le locus de contrôle (de l'anglais, *locus of control*). Il se définit comme la tendance que les individus ont à considérer que les événements qui les affectent sont le résultat de leurs actions ou, au contraire, qu'ils sont le fait de facteurs externes (e.g. la chance, les autres, un Dieu) sur lesquels ils n'ont que peu d'influence (Rotter (1954), p.2 et Rotter (1966)). Ainsi, pour un individu ne percevant aucune relation entre son comportement et les résultats obtenus, on parlera de locus de contrôle externe. Si, à l'inverse, l'individu perçoit une relation directe entre son comportement et les résultats obtenus, on parlera de locus de contrôle interne.

Cette perception du contrôle est mesurée en utilisant l'échelle de Rotter. Les individus doivent mentionner leur degré d'accord avec les dix items contenus dans cette échelle[5]. L'échelle se compose en deux dimensions représentant ainsi la distinction binaire interne/externe. La première dimension est mesurée par 3 items (I. 1, I. 6 et I. 9), la seconde dimension est mesurée par 7 items (I. 2, I. 3, I. 4, I. 5, I. 7, I. 8, I. 10). Le tableau suivant reprend l'ensemble des items en les classant selon qu'ils se réfèrent au locus de contrôle interne ou au locus de contrôle externe.

[5]Ils le font en renseignant une réponse variant de 1 ("je ne suis pas du tout d'accord") à 7 ("je suis complétement d'accord") pour chacun des 10 items.

Tableau 1 : L'échelle du locus de contrôle

Items liés au locus de contrôle interne	I. 1. Le cours de ma vie dépend de moi
	I. 6. Le succès demande beaucoup de travail
	I. 9. Les capacités cognitives sont plus importantes que le niveau d'effort
Items liés au locus de contrôle externe	I. 2. Je n'ai pas obtenu ce que je méritais
	I. 3. Ce que l'on obtient dépend de la chance
	I. 4. Les conditions sociales influencent fortement la réussite
	I. 5. Les autres prennent des décisions importantes dans ma vie
	I. 7. Je doute de mes capacités quand des problèmes surviennent
	I. 8. Les possibilités de réussite sont définies par les conditions sociales
	I. 10. Je n'ai que peu de contrôle sur ma vie

Source: Rotter (1954, 1966); Borghans et al. (2008); et Almlund et al. (2011).

1.2. ... et les préférences économiques...

Les préférences économiques comprennent les préférences sociales et les préférences vis-à-vis du risque et du temps. Nous ne développerons que les deux dernières.

L'aversion au risque est définie par la désutilité que procure la dispersion d'une variable aléatoire (Rothschild and Stiglitz (1970); Crainich et al. (2014); Beaud and Willinger (2016)). Il n'existe pas de consensus sur la meilleure manière de la mesurer. Nous avons donc retenu trois méthodes différentes pour classer les individus selon leur tolérance vis-à-vis du risque.

La première méthode est celle proposée par Holt and Laury (2002). Elle consiste en une liste de choix entre deux loteries : une loterie peu risquée (loterie A) et une loterie plus risquée (loterie B). Les gains associés à chaque loterie restent inchangés tout au long de la liste, seules les probabilités associées à ces gains varient. Par exemple, dans la loterie A, les gains seront toujours de 32 ou de 40 euros. Dans la loterie B, les gains seront toujours de 2 ou de 77 euros. Ainsi, les loteries A et B sont respectivement qualifiées de moins et de plus risquée car la distribution des gains de la loterie A est moins dispersée – ou étalée – que celle de la loterie B. Typiquement, un individu averse au risque devrait commencer par choisir la loterie A (au moins pour les quatre premiers possibilités), puis la loterie B à partir d'un certain seuil, et de maintenir ce choix jusqu'à la dernière possibilité. En d'autres termes, plus un individu est hostile au risque, et plus ce point de basculement vers la loterie B est tardif. Sous l'hypothèse que l'aversion relative au risque est constante (CRRA), chaque réponse correspond à un intervalle du paramètre d'aversion relative pour le risque. Ceci est représenté dans le tableau 1. La première partie du tableau se réfère à des loteries avec des gains faibles et la seconde partie de ce tableau se réfère à des loteries proposant des gains plus importants.

Par ailleurs, avant de faire leur choix, les participants sont informés qu'une seule question sera sélectionnée au hasard pour déterminer leur gain. Ceci permet de mieux représenter la véracité de leur choix (e.g. Eckel and Grossman (2002); Eckel and Grossman (2008a)).

Tableau 2 : Loteries à la Holt and Laury (2002)

Loteries à gains faibles

Loterie de type A				Loterie de type B				Intervalle de CRRA	
P	Euros	(1-p)	Euros	P	Euros	(1-p)	Euros	Limite inférieure	Limite supérieure
0.1	40	0.9	32	0.1	77	0.9	2	-∞	-1.71
0.2	40	0.8	32	0.2	77	0.8	2	-1.71	-0.95
0.3	40	0.7	32	0.3	77	0.7	2	-0.95	-0.49
0.4	40	0.6	32	0.4	77	0.6	2	-0.49	-0.14
0.5	40	0.5	32	0.5	77	0.5	2	-0.14	0.15
0.6	40	0.4	32	0.6	77	0.4	2	0.15	0.41
0.7	40	0.3	32	0.7	77	0.3	2	0.41	0.68
0.8	40	0.2	32	0.8	77	0.2	2	0.68	0.97
0.9	40	0.1	32	0.9	77	0.1	2	0.97	1.37

Loteries à gains élevés

Loterie de type A				Loterie de type B				Intervalle de CRRA	
P	Euros	(1-p)	Euros	P	Euros	(1-p)	Euros	Limite inférieure	Limite supérieure
0.1	100	0.9	40	0.1	180	0.9	2	$-\infty$	-0.75
0.2	100	0.8	40	0.2	180	0.8	2	-0.75	-0.32
0.3	100	0.7	40	0.3	180	0.7	2	-0.32	-0.05
0.4	100	0.6	40	0.4	180	0.6	2	-0.05	0.16
0.5	100	0.5	40	0.5	180	0.5	2	0.16	0.34
0.6	100	0.4	40	0.6	180	0.4	2	0.34	0.52
0.7	100	0.3	40	0.7	180	0.3	2	0.52	0.70
0.8	100	0.2	40	0.8	180	0.2	2	0.70	0.91
0.9	100	0.1	40	0.9	180	0.1	2	0.91	1.20

La seconde méthode est celle proposée par Binswanger (1980). Les participants doivent sélectionner une option parmi les six proposées. Toutes les options sont binaires (un choix entre un gain faible et un gain élevé) et symétriques en probabilité (chacun des gains à une probabilité de succès de 50 %). Les options offrent les gains suivants : A = (28 ; 28), B = (24 ; 36), C = (20 ; 44), D = (16 ; 52), E = (12 ; 60) et F = (2 ; 70). En fonction de son choix, l'individu peut être catégorisé selon son niveau de risque : A s'il est extrêmement, B s'il est en fortement, C s'il est moyennement, D s'il est modérément hostile au risque, E s'il est neutre au risque (ou légèrement hostile), et F s'il est attiré par le risque. En se référant au modèle d'espérance d'utilité et sous l'hypothèse de CRRA, on peut faire correspondre chaque choix à un intervalle pour le paramètre d'aversion relative pour le risque. Le tableau 3 donne une représentation visuelle de cette méthode.

Tableau 3 : Loterie à la Binswanger (1980)

	Gain				Intervalle de CRRA	
	Bas	Haut	Espérance de gain	Variance	Limite inférieure	Limite supérieure
A	28	28	28	0	3.36	$+\infty$
B	24	36	30	8.5	1.16	3.46
C	20	44	32	17	0.71	1.16
D	16	52	34	25.5	0.499	0.71
E	12	60	36	33.9	0	0.499
F	2	70	36	48.1	$-\infty$	0

La troisième et dernière méthode consiste à mesurer non plus les préférences, mais les attitudes vis-à-vis du risque (e.g. Dohmen et al. (2011)). Pour ce faire, nous utilisons trois questions. Celles-ci portent sur les attitudes vis-à-vis du risque en général, en santé et en finance. L'individu doit répondre à la question “sur une échelle d'importance de 0 à 10, vous considérez-vous comme quelqu'un de prudent, limitant au maximum les risques ; ou inversement comme quelqu'un qui aime prendre des risques qui aime l'aventure et recherche la nouveauté et les défis ?[6]”. Les mêmes questions, mais déclinées pour la santé et la finance, sont proposées.

Les préférences vis-à-vis du temps sont mesurées par le taux d'escompte individuel (e.g. Coller and Williams (1999); Harrison et al. (2002)). Pour mesurer ces préférences, nous utiliserons une méthode reposant sur une liste de choix successifs entre deux montants accessibles, l'un dans un futur proche, l'autre dans un futur lointain. Cette liste est composée de 15 choix. À chacun des choix sont associés une option A et une option B. Les options B offrent des gains plus importants, mais disponibles plus tard (ici avec un délai de deux mois). Les options A offrent, à l'inverse, des gains moins importants, mais disponible plus rapidement (ici avec un délai d'un mois). En d'autres termes, avec l'option A, un gain de 100 euros sera disponible dans 1 mois, avec l'option B un montant de 100 euros + x sera disponible dans 2 mois. Les options A sont toutes identiques et donc restent inchangées tout au long de la liste, alors que les options B, la valeur de x augmente tout au long de la liste.

[6] Sur cette échelle les individus très prudents répondront un chiffre proche de 0, ceux qui aiment prendre des risques, un chiffre proche de 10.

Ainsi, un individu relativement impatient devrait commencer par choisir les options A, puis les options B à partir d'un certain seuil et maintenir ce choix jusqu'à la dernière question. On peut alors interpréter l'impatience comme le passage le plus tardif possible de l'option A vers l'option B. A l'inverse, plus un individu est patient et plus le passage de l'option A vers l'option B se produira tôt. Par ailleurs, comme pour la préférence vis-à-vis du risque, une seule question sera sélectionnée au hasard pour déterminer le paiement du répondant. Le tableau 4 illustre notre méthode de mesure des préférences temporelles basée sur Coller and Williams (1999).

Tableau 4 : Loterie à la Coller and Williams (1999)

Option A (dans un mois)	Option B (dans deux mois)	Quelle option préférez-vous ?	
100 €	100.42 €	A	B
100 €	100.83 €	A	B
100 €	101.25 €	A	B
100 €	101.67 €	A	B
100 €	102.08 €	A	B
100 €	102.50 €	A	B
100 €	103.33 €	A	B
100 €	104.17 €	A	B
100 €	105.00 €	A	B
100 €	106.67 €	A	B
100 €	108.33 €	A	B
100 €	112.50 €	A	B

1.3. ... sont des paramètres distincts mais complémentaires

Les préférences et les attitudes vis-à-vis du risque et du temps sont à la fois corrélées entre elles et également avec certains traits de personnalité. Néanmoins, ils restent des paramètres bien distincts, comme en témoigne la synthèse de la littérature sur le sujet.

L'étude pionnière, celle de Almlund et al. (2011), propose une association intuitive entre différents traits de personnalité et les préférences économiques. En liant la définition de certains traits de personnalité avec celles des préférences économiques, les auteurs montrent que le fait d'être consciencieux, d'avoir la maîtrise de soi et de considérer le futur sont tous des traits associés aux préférences vis-à-vis du temps. L'ouverture d'esprit et l'impulsivité seraient plutôt associées à la préférence vis-à-vis du risque.

S'agissant d'études empiriques portant sur la corrélation entre ces deux paramètres, les résultats sont hétérogènes.

Concernant le lien entre préférences vis-à-vis du temps et les traits de personnalité, Daly et al. (2009) trouvent une corrélation négative entre les taux d'escompte dans le domaine financier et le fait d'être consciencieux. Ces résultats sont obtenus en utilisant un échantillon d'étudiants dublinois. Sur populations générales, à l'inverse, Andersen et al. (2014) décèlent une corrélation positive entre l'amabilité et le taux d'escompte individuel. Néanmoins, cette étude ne porte pas sur un échantillon représentatif, mais sur des conducteurs américains de poids lourds. Lorsqu'un échantillon représentatif est considéré, comme c'est le cas de Dohmen et al. (2005) pour la population allemande, aucune corrélation significative n'est trouvée.

S'agissant du lien entre tolérance au risque et traits de personnalité, Dohmen et al. (2005) trouvent une corrélation négative entre une telle tolérance et l'ouverture d'esprit et l'amabilité. Cette corrélation négative est aussi retrouvée par les travaux de Hirsh and Inzlicht (2008) et de Rustichini et al. (2016). Les premiers en utilisant des données provenant d'étudiants en psychologie de l'Université de Toronto, les seconds en utilisant un échantillon non-représentatif de la population américaine. Ces auteurs montrent que la tolérance au risque est inversement reliée à la névrose et au fait d'être consciencieux. Ces résultats ne sont néanmoins pas partagés par Bibby and Ferguson (2011) et Rustichini et al. (2016) qui trouvent une corrélation positive entre la tolérance au risque et la névrose et l'amabilité. Les résultats de l'étude de Andersen et al. (2014) corroborent avec ceux de Bibby and Ferguson (2011) et de Rustichini et al. (2016) : la tolérance au risque est positivement corrélée à la névrose. Enfin, Eckel and Grossman (2002) ne trouvent aucune association significative entre l'aversion au risque et les traits de personnalité en utilisant des données expérimentales d'étudiants américains.

En résumé, même si les traits de personnalité et les préférences économiques semblent conceptuellement liés, leur association empirique ne fait pas l'objet d'un consensus (Becker et al. (2012)[7]. Ceci pourrait être dû à des échantillons différents, à des mesures des préférences et des traits qui sont spécifiques à chaque étude, ou encore dû à des méthodes d'estimations différentes.

Les travaux portant sur le lien entre les préférences économiques entre elles montrent des résultats moins contrastés : il existerait une corrélation négative stable entre la tolérance au risque et l'impatience. En d'autres termes, plus un individu est tolérant au risque, plus il serait patient. Ceci à notamment été mis en évidence par plusieurs études expérimentales (e.g. Anderhub et al. (2001); Burks et al. (2009); Dohmen et al. (2011)). À titre d'exemple, Dohmen et al. (2011) ont montré que ces deux dimensions étaient corrélées en utilisant un échantillon de plus de 1000 individus représentative de la population allemande.

Ces deux paramètres étant corrélés, donc liés, il est donc difficile d'établir une relation causale entre l'un de ces paramètres et, par exemple, un comportement de santé. Pour illustrer cette difficulté, Heckman and Kautz (2012) ont utilisé un modèle de production de santé. Dans ce modèle, la santé est une fonction de plusieurs paramètres (dont le revenu et le niveau d'éducation), mais aussi des traits de personnalité et d'un niveau d'effort pour produire cet état de santé. Or, ce niveau d'effort dépend lui-même des préférences économiques de l'individu. Ceci explique en partie la difficulté d'obtenir une relation causale[8].

Malgré cette difficulté, plusieurs études empiriques ont pointé un soupçon de causalité (ou une très forte corrélation) entre plusieurs comportements avec les préférences économiques et les traits de personnalité.

2. Les traits et les préférences : déterminants de nombreux comportements

2.1. La perception du contrôle

Les individus ayant les mêmes caractéristiques socio-économiques n'agissent pas toujours de la même façon. Une des explications pour expliquer ces différences vient de leur per-

[7] Néanmoins, il semble que l'aversion au risque soit corrélée avec le niveau de névrose d'un individu ; et que le fait d'être consciencieux soit corrélé avec la patience.

[8] Pour plus de détail sur l'incorporation des traits de personnalité dans les modèles économiques, le lecteur peut se référer à Cunha et al. (2010) et à Almlund et al. (2011).

sonnalité et de la manière dont ils pensent avoir le contrôle sur les événements de leur vie. La littérature en économie donne quelques indications sur la manière dont cette perception influence les décisions de travail, de santé et les choix d'études des individus.

Comme indiquée dans la première section de cette introduction, la mesure la plus souvent utilisée pour étudier la perception du contrôle est le locus de contrôle (LOC). Nous allons donc nous référer aux études ayant utilisé ce concept.

Concernant le lien entre les décisions sur le marché du travail et le LOC, les résultats sont convergents quant à l'effet de la perception du contrôle. Les individus ayant un LOC interne sont plus à même de rechercher activement du travail et ont donc des temps de chômage plus court que les individus ayant un LOC externe (Caliendo et al. (2010); Cobb-Clark and Tan (2011); McGee (2015); McGee and McGee (2016)). Les individus ayant un LOC externe ont, en moyenne, des exigences salariales moins importantes (Cebi (2007); Semykina and Linz (2007); Heineck and Anger (2010); Salamanca et al. (2013)) que leurs homologues ayant un LOC interne. En conséquence, les individus "internes" ont des salaires plus élevés que les individus "externes".

Ces différences de salaires peuvent aussi venir des choix d'études. En effet, les individus avec un LOC interne ont des niveaux d'études plus importants que les individus avec un LOC externe (Feinstein (2000); Flouri (2006)). Les salaires faisant partie des ressources de l'individu, il n'est pas surprenant de voir que les individus ayant un LOC interne ont des comportements d'investissements et d'épargnes différents de ceux ayant un LOC externe. Ainsi, les individus attribuant une relation causale entre leurs actions et ce qui leur arrive investissent plus dans des actifs risqués et épargnent plus (Salamanca et al. (2013); Cobb-Clark et al. (2016)) que ceux qui pense que ce qui leur arrive est dû à des facteurs extérieurs.

S'agissant des comportements de santé, la littérature est également sans équivoque : les individus "internes" ont de meilleurs comportements de santé que les "externes". Ils vont notamment manger plus équilibré, pratiquer plus régulièrement une activité physique ou sportive, vont avoir une consommation modérée d'alcool et font faire plus régulièrement des visites médicales (Chiteji (2010); Cobb-Clark et al. (2014); Conell-Price and Jamison (2015)).

2.2. Les préférences et les attitudes vis-à-vis du risque et du temps

À mêmes caractéristiques socio-économiques, les préférences et les attitudes vis-à-vis du temps et du risque sont des variables importantes expliquant les choix des individus. À l'inverse des traits de personnalité ou la littérature économique n'est qu'émergente, celle sur les préférences économiques a produit une grande quantité d'études. Nous ne faisons donc pas honneur à la littérature en ne citant ici qu'une brève partie des travaux sur le sujet.

Comme pour les traits de personnalité, les préférences et les attitudes vis-à-vis du risque et du temps sont liées avec des décisions sur le marché du travail et avec des comportements de santé.

Les préférences et les attitudes vis-à-vis du temps et du risque sont des déterminants de nombreuses décisions sur le marché du travail. Elles sont en lien avec le choix du métier – notamment celle de devenir auto-entrepreneur ou d'être un travailleur indépendant - (Van Praag and Cramer (2001); Cramer et al. (2002); Ekelund et al. (2005); Fuchs-Schundeln (2005); Bonin et al. (2007); Dohmen et al. (2011); Skriabikova et al. (2014); Koudstaal et al. (2015); Fossen and Glocker (2017)), avec les attentes salariales des chômeurs et des actifs (Shaw (1996)), avec le niveau de salaire (Budria et al. (2013); Pannenberg (2010)), avec la mobilité professionnelle (Meier (2010)) et avec le type de contrat de travail signé (Guiso (2004)).

Les préférences et les attitudes vis-à-vis du temps et du risque sont aussi des déterminants des comportements de santé. Elles déterminent, en partie, les décisions de consommation de tabac (Barsky et al. (1997); Harrison et al. (2002); Khwaja et al. (2006); Chabris et al. (2008); Scharff and Viscusi (2011); Lawless et al. (2013); Brown and van der Pol (2014); Bradford et al. (2015)), d'alcool (Anderson and Mellor (2008); Van Der Pol (2011); Andersen et al. (2014); Bradford et al. (2015)) et de la consommation de drogues comme la cocaïne et l'héroïne (Kirby (2004); Blondel et al. (2007)). Ces préférences vont aussi impacter le poids (Komlos et al. (2004): Lusk and Coble (2005)), les habitudes alimentaires des individus (Galizzi and Miraldo (2017)), leur demande de tests médicaux (Picone (2004)) et de vaccins (Chapman and Coups (1999); Nuscheler (2016)). Enfin, les préférences et les attitudes vis-à-vis du temps et du risque influencent aussi l'observance des traitements (Brandt (2013); Van Der Pol et al. (2017)).

3. Les traits et les préférences sont-ils des paramètres stables ?

Dans Le crépuscule des idoles (1988), Nietzsche écrivait : "Tout ce qui ne tue pas, rend plus fort". Cette maxime va servir de leitmotiv aux trois sous-parties proposées ci-dessous. Toutes ont questionné la stabilité des traits et des préférences. Nous proposons un regard croisé de la biologie, de la psychologie et de l'économie sur cette question.

3.1. Contributions de la biologie

Dans cette sous-partie nous allons reporter quelques études montrant la manière dont la biologie et la neurologie ont documenté les changements de la personnalité. Ces changements vont s'opérer suite à une lésion cérébrale qui va, soit détériorer certaines parties du cerveau soit, altérer sa composition chimique.

Les deux parties du cerveau qui régulent la personnalité d'un individu sont l'amygdale et la partie ventro-médiane du cortex pré-frontal. L'amygdale répond aux stimulations immédiates, comme le danger et la peur. À l'inverse, le cortex pré-frontal est la partie raisonnée du cerveau, celle qui prend des décisions plus rationnelles. Lorsqu'un individu veut faire un choix, ces deux parties du cerveau vont entrer concurrence. Le signal le plus fort, commande le comportement. Ainsi, un individu avec une lésion détériorant l'amygdale devrait agir de manière plus calme et posée. À l'inverse, une lésion abîmant le cortex pré-frontal devrait conduire l'individu à faire des choix plus impulsifs en surévaluant les valorisations immédiates (Bechara (2005); Monterosso and Luo (2010)).

Pour ne citer qu'un exemple, des patients ayant eu une lésion cérébrale au niveau du cortex pré-frontal (cerveau empalé par une hélice en métal) ont eu des difficultés à planifier et sont devenu plus irascibles (Mataró et al. (2001); Damasio et al. (2005)). Ces changements de comportement semblent être persistant au moins jusqu'à 5 ans après le traumatisme (Lezak (1987)).

Par ailleurs, des changements dans la composition chimique du cerveau peuvent aussi entraîner une modification de la personnalité de l'individu. Ceci est notamment le cas pour les sujets prenant des traitements anti-dépressifs (e.g. Tang et al. (2009)). Ces traitements peuvent, notamment, rendre l'individu plus extraverti.

3.2. Contributions de la psychologie

La manière d'appréhender la stabilité en psychologie se fait en analysant les changements de traits de personnalité d'individus ayant subi un ou des événements de vie traumatisant.

Introduit par Tedeschi and Calhoun (2004), le terme consacré à l'évolution de ces traits est la croissance post-traumatique (de l'anglais, *post-traumatic growth* - PTG). Les auteurs définissent la PTG comme l'expérience de changements positifs significatifs découlant des efforts d'adaptation d'un individu faisant face à un événement traumatisant. Ces changements pouvant être de quatre ordres : le développement de relations plus intimes avec son entourage, connaître de nouvelles expériences, un engagement pour les questions relatives à l'existence humaine, et une appréciation plus grande de la vie (e.g. Tedeschi and Calhoun (1996); Tedeschi and Calhoun (2004)).

Les événements de vie traumatisant utilisés dépendent de type d'échantillon utilisé (Gray et al. (2004)). Lorsque les études se font sur des sujets étudiants, les événements de vie inclus principalement des accidents de la circulation (Calhoun et al. (2000)). Pour les études utilisant des populations adultes, les auteurs ont recours au diagnostic d'une maladie grave, à la survenue d'une catastrophe naturelle, aux attaques physiques ou encore aux maladies chroniques (Helgeson et al. (2006); Tennen and Affleck (2009)). Pour mesurer la PTG, la littérature se réfère en général à l'index de la croissance post-traumatique développé par Tedeschi and Calhoun (1996). Cet index contient des questions sur les quatre domaines évoqués plus haut et les répondants doivent indiquer sur une échelle de 6 points le degré avec lequel ils ont changé.

Les quelques études utilisant des données longitudinales indiquent que 58 à 79 % des individus ont reporté des changements positifs (Affleck et al. (1987); Affleck and Tennen (1996); McMillen et al. (1997); Sears et al. (2003)). De plus, il semblerait que ces changements s'inscrivent dans la durée (Bauer and Bonanno (2001); Srivastava et al. (2003)). D'autres travaux portant spécifiquement sur les Big-Five ont montré que les individus ayant eu un cancer du poumon, par exemple, se sont montrés plus extravertis et plus aimables (Hoerger et al. (2014)). Les raisons de ces changements sont moins connues, même si l'hypothèse d'une volonté d'affirmation de soi semble être mentionnée par plusieurs études (Tennen and Affleck (2009)).

3.3. Contributions de l'économie

En économie, la théorie traditionnelle fait l'hypothèse que les traits et les préférences sont des paramètres stables (Friedman (1953); Stigler and Becker (1977)). Néanmoins, certaines études empiriques viennent nuancer cette hypothèse.

Une première partie de la littérature économique a documenté l'association entre plusieurs événements de vie et le LOC en utilisant deux cohortes de panels annuels : le HILDA (de l'anglais, *Household Income and Labor Dynamics in Australia*) et le G-SOEP (de l'anglais, *German Socio-Economic Panel*).

En utilisant le HILDA, Cobb-Clark and Schurer (2013) ont montré que le LOC pouvait se modifier, à le moyen terme (i.e. 4 ans), suite à certains événements de vie. Néanmoins, les changements observés étaient modestes et concentrés chez les individus les plus âgés. Les auteurs distinguent les événements de vie ayant conduit à rendre les individus plus "internes", de ceux les ayant rendus plus "externes". Ainsi, une promotion professionnelle, un changement de travail ou une augmentation de leurs revenus ont rendu les individus plus "internes". À l'inverse, la naissance d'un enfant, la maladie d'un proche, ou une baisse des revenus les a rendu plus "externes". D'autres événements de vie sont étudiés (i.e. la mort du partenaire, être retraité, ou être victime d'une agression physique) mais aucun d'entres eux n'ont impacté significativement la perception du contrôle.

Une seconde partie de la littérature a analysé le lien entre événements de vie et tolérance au risque. Ceci est fait en utilisant le G-SOEP et le HRS (de l'anglais, *Health and Retirement Survey*) – un échantillon non-représentatif de la population américaine.

En utilisant 10 années du HRS, Sahm (2012), montre qu'un événement important de santé (i.e. une crise cardiaque, un accident vasculaire cérébrale (AVC) ou un cancer du poumon) provoque une très légère baisse de la tolérance vis-à-vis du risque. L'auteure conclue que la tolérance au risque varie d'un individu à l'autre, mais ne varie pas pour un même individu. Schurer (2015) en utilisant 7 années du G-SOEP montre que ces variations inter-individuelles sont plus importantes pour les personnes âgées de 35 à 45 ans. Tout comme Schurer (2015), Decker and Schmitz (2016) utilisent le G-SOEP pour étudier si un événement de santé – mesuré par une perte dans la force de pression – modifie la tolérance au risque. Les résultats montrent que cet événement induit une augmente de l'aversion au risque chez les individus le subissant. Une étude récente de Jones et al. (2018) croise les traits de personnalité avec la tolérance au risque. Ils concluent que les personnes extraverties sont plus tolérantes au risque que les autres après avoir fait face à un événement de santé (mesuré par un cancer, un AVC, un diabète, une hypertension artérielle, ou un problème psychiatrique).

Il semble donc que la perception du contrôle et la tolérance au risque puissent être des paramètres instables.

4. Définition et impact des événements de santé

4.1. Définition

Un choc de santé est un événement en lien avec une pathologie se manifestant au niveau individuel. Analyser ces événements est important car la plupart des individus vont en connaître au cours de leur existence. En effet, dans les trois pays analysés ici (l'Allemagne, l'Angleterre et la France), près de 20 % de leurs populations ont connu des chocs aigûes (e.g. crise cardiaque, AVC) ou chroniques (e.g. diabètes, cancer, dépression) de santé.

Les économistes de la santé ont utilisé plusieurs types d'événements de santé – résumé dans le tableau 4 – pour mesurer les chocs de santé. Ils diffèrent selon la possibilité, ou non, de les nommer. Quand les événements sont identifiés, la littérature fait référence à 3 événements majeurs (i.e. un cancer, un problème cardiaque ou un AVC) et à 4 événements mineurs (i.e. diabète, hypertension artérielle, la dépression et l'anxiété). Quand les événements ne sont pas identifiés, la littérature propose 4 types de proxy : une baisse de la santé auto-évaluée, une hospitalisation, la survenue d'une maladie grave, ou une perte dans la force de pression. Il y a donc 15 mesures utilisées pour mesurer un choc de santé.

Tableau 4 : Types d'événements de santé

	Sous-groupes	Types d'événements de santé	Nombre d'étude
Identifié	Evénements majeurs	Cancers, problèmes cardiques, AVC.	12
	Evénements mineurs	Diabetes, hyper tension artérielle, problèmes psychiatriques.	12
Non-identifié	Baisse de la santé auto-évaluée		9
	Hopistalisation		5
	Survenue d'une maladie grave		2
	Perte dans la force de pression		1

Note: Les cancers comprennent des cancers du sein et du poumon. Les problèmes cardiaques incluent des crises cardiaques, des infarctus du myocarde et les maladies cardiovasculaires. Les problèmes psychiatriques inclus les dépressions et les troubles de l'anxiété. La distinction retenue entre événements majeurs et mineurs est celle de Cheng (2019).

4.2. Population touchée

La population touchée par les différents chocs de santé est principalement centrée auprès des sujets âgés (i.e. de plus de 50 ans), à l'exception du diabète et des problèmes psychiatriques qui peuvent affecter tous les âges. A contrario, les mesures utilisant des proxies, sont des chocs pouvant affecter tous les individus. Par ailleurs, ces deux types de mesure sont utilisés pour mesurer les chocs de santé dans les pays développés (i.e. les Etats-Unis, l'Australie, l'Autriche, la Belgique, Le Danemark, la France, l'Allemagne, la Grèce, l'Italie, le Portugal, les Pays-Bas, l'Espagne, la Suède, la Suisse et le Royaume-Unis). Les populations et les échantillons utilisés sont reportés dans le tableau 5.

Tableau 5 : Populations et échantillons étudiés

Sous-groupes	Pays	Echantillon
Evénements majeurs	Etats-Unis	Individus âgés de 51-61 ans (HRS) Individus âgés de 51 et plus (HRS) Hommes âgés de 20-64 ans (MEPS) Individus âgés de 40-70 ans (PSID) Femmes âgées de 26-64 ans (HRS)
	l'Autriche, la Belgique, Le Danemark, la France, l'Allemagne, la Grèce, l'Italie, le Portugal, les Pays-Bas, l'Espagne, la Suède	Individus âgés de 50 ans et plus (SHARE) ou individus âgés de 16 ans et plus (GSOEP)
Evénements mineurs	Etats-Unis	Individus âgés de 51-61 ans (HRS) Hommes âgés de 20-64 ans (MEPS)
	Angleterre	Individus âgés de 15 ans et plus (BHPS)
	Allemagne	Individus âgés de 16 ans et plus (GSOEP)
Baisse de la santé auto-évaluée	Allemagne	Individus âgés de 16 ans et plus (GSOEP)
	La Belgique, Le Danemark, la France, l'Allemagne, la Grèce, l'Italie, le Portugal, les Pays-Bas, l'Espagne, la Suède	Individus âgés de 16 ans et plus (ECHP)
	Angleterre	Individus âgés de 16 ans et plus (BHPS)
	Espagne	Individus âgés de moins de 60 ans (ECHP)
Hospitalisation	Suède	Individus âgés de 30-59 ans (LOUISE + NPR)
	Angleterre	Individus âgés de 15-40 ans (NCDS)
	Pays-Bas	Individus âgés de 18-64 ans (GBA)
Survenue d'une maladie grave	Australie	Individus âgés de 15 ans et plus (HILDA)
	Etats-Unis	Individus âgés de 45-70 ans (HRS)
Perte de la force de pression	Allemagne	Individus âgés de 16 et plus (GSOEP)

Note: GSOEP vient de *German Socioeconomic Panel*; HRS vient *Health and Retirement Study*; SHARE vient de *Survey of Health Ageing and Retirement in Europe*; BHPS vient de *British Household Panel Survey*; HILDA vient de *Household, Income and Labour Dynamics in Australia*; MEPS vient de *Medical Expenditure Panel Survey*; ECHP vient de *European Community Household Panel*; LOUISE vient *population register covering demographic and socioeconomic information*; NPR est le *National Patient Register*; NCDS vient de *British National Child Development Study*; GBA vient de *Municipality Register*; et PSID vient de *Panel Study of Income dynamics*. Ils s'agit toujours de données longitudinales.

4.3. Comportements impactés

Les conséquences des chocs de santé vont bien au-delà du secteur sanitaire : ils impactent également les décisions sur le marché du travail et la richesse de l'individu. Plus précisément, un nombre de 15 études empiriques ont exploré la relation entre chocs de santé et décisions sur le marché du travail, 10 avec les comportements de santé et 3 avec la richesse.

La littérature portant sur la relation entre chocs de santé et comportement sur le marché du travail s'articule autour de deux grands aspects : la participation sur le marché du travail, et comment cette participation varie en fonctions des caractéristiques socio-économiques de l'individu.

S'agissant de la participation sur le marché du travail, les études montrent toutes un impact significatif des chocs de santé sur la probabilité d'être au chômage (e.g. Riphahn (1999); Garcia Gomez and Lopez Nicola (2006); McGeary (2009); Garcia-Gomez (2011); Conley and Thompson (2013); Bradley et al. (2013); Garcia-Gomez et al. (2013); Jones et al. (2015); Zimmer (2015); Trevisan and Zantomio (2016); Jones et al. (2016)), sur les temps de travail (e.g. Cai et al. (2014)) et sur un passage précoce à la retraite (Hagan (2009); Sanchez et al. (2019)).

La seconde partie de la littérature montre que cet effet négatif dépend de certaines caractéristiques de l'individu, comme le sexe, le niveau initial de revenu et le niveau d'études. Ainsi, Lindeboom et al. (2007) trouvent que les taux d'emploi des hommes sont réduits de 23 points de pourcentage suite à un choc de santé. Cette baisse n'est que de 12 points de pourcentage pour les femmes. De plus, la nature du choc importe : les femmes sont plus à même de partir précocement à la retraite suite à un cancer, alors que c'est après une arthrite pour les hommes (McGeary (2009)). Il est aussi plus probable pour les épouses de commencer ou de continuer à travailler si leur mari subit un choc de santé. Les époux, sont quant à eux, plus à même de se retirer du marché du travail si leur femme subit un choc de santé (Wu (2003); Garcia-Gomez et al. (2013)).

Smith (1999) montre que si les revenus d'avant-choc sont au-dessous du niveau médian du revenu de l'échantillon, alors ces ménages ont une perte de richesse plus grande que les autres. Garcia-Gomez et al. (2013) trouvent des résultats similaires : les individus ayant de faibles revenus souffrent davantage des conséquences négatives du choc de santé que les individus à hauts revenus. S'agissant du niveau d'éducation, Lundborg et al. (2015) montrent que l'effet du choc de santé est plus grave pour les moins éduqués que pour les plus éduqués. Plus précisément, les taux d'emplois à l'âge de 40 ans pour les travailleurs les moins éduqués sont réduits de 21 points de pourcentage, alors qu'il n'est que de 9 points de pourcentage pour les travailleurs plus éduqués.

Concernant l'effet de négatif des chocs de santé sur la richesse, peu d'études sont disponibles à l'heure actuelle. Smith et al. (2001) et Coile and Milligan (2009) montrent que les chocs de santé sont associés à une diminution de la détention d'actifs financiers (e.g. être le détenteur principal de sa voiture ou de sa maison) et que cet effet se renforce à mesure que le temps passe. Lee and Kim (2008), cependant, notent que l'effet négatif du choc de santé sur la richesse de l'individu tend à se résorber pour les seniors.

La littérature empirique a montré qu'il existe une certaine homogénéité des effets de différents chocs de santé sur les comportements de santé des individus. Les individus ayant subi de tels chocs, quelle qu'en soit leur nature, adoptent de meilleurs comportements de santé. Par ailleurs, si ce choc ne les touche pas directement (i.e. si le choc est subi par un individu de leur entourage), leurs comportements de santé ne sont pas impactés.

La première étude date des années 2000 et montre que les fumeurs ayant eu un cancer du poumon ou une maladie cardio-vasculaire réduisent significativement leur espérance de vie subjective. Ils présument en effet qu'ils auront une probabilité plus faible de vivre jusqu'à 75 ans ou plus que des fumeurs n'ayant pas subi de choc. Les auteurs obtiennent ce résultat en utilisant un panel d'individus américains âgés de 51 à 61 ans (Smith et al. (2001)). La persistance de cet effet peut, néanmoins, être questionnée car l'horizon étudié n'est que de deux ans. Baji and Biro (2018) poursuivent le travail de Smith et al. (2001) en utilisant les mêmes individus et les mêmes chocs de santé, mais sur une période de 6 ans. Ils montrent que trois ans après avoir reçu le diagnostic de leur maladie, les individus retrouvent la même espérance de vie subjective qu'avant la maladie. Il semble donc que les chocs de santé ont un impact négatif, mais transitoire, sur l'espérance de vie subjective des individus.

S'agissant de la santé objective, les résultats de Clark and Etilé (2002) montrent que les fumeurs ayant eu une oppression thoracique ou au cœur, ou une baisse de leur niveau de santé auto-déclarée réduisent leur consommation de tabac par rapport aux fumeurs ne subissant pas ces chocs. Ceci est obtenu à partir d'une cohorte anglaise de près de 2 000 individus âgés de 25 à 65 ans suivis pendant 5 ans. Sundmacher (2012) trouve un résultat similaire à ceux de Clark and Etilé (2002) mais sur les données d'un panel allemand. Les individus fumeurs ayant subi un choc de santé, c'est-à-dire une baisse de leur santé auto-déclarée, augmentent leur probabilité d'arrêter de fumer l'année du choc. L'auteur étend la précédente étude à la fois en prenant un horizon temporel plus long (10 ans) et un échantillon plus large d'individus (16 ans et plus). Darden et al. (2018) précise que la réduction de la consommation de tabac dépend de la gravité du choc subi : les fumeurs sont sensibles aux cancers et aux maladies cardio-vasculaires, mais ne le sont pas à des changements de bio-marqueurs cardio-vasculaires (comme par exemple la variation de la pression artérielle ou le taux de cholestérol). Enfin, ces résultats sont aussi confirmés au niveau de 11 pays européens[9] par Richards and Marti (2014), qui montrent qu'après le diagnostic d'une maladie cardio-vasculaire, les fumeurs réduisent leur probabilité de fumer. Cet effet est d'autant plus marqué que les individus ont des niveaux de revenus faibles et qu'ils ont une faible couverture maladie. Ces résultats sont obtenus en utilisant des données longitudinales d'individus âgés d'au moins 50 ans et suivis pendant 3 ans.

D'autre part, les fumeurs dont des proches ont eu un choc de santé n'ont pas changé leur consommation de tabac. Ceci est vrai pour le partenaire (Clark and Etilé (2002); Khwaja et al. (2006)), et pour les parents du fumeur (Darden et al. (2018)), que le choc soit un cancer du poumon, une maladie cardio-vasculaire, ou une baisse de leur niveau de santé auto-déclarée.

En résumé, même si les types de chocs, les échantillons et les stratégies économétriques utilisées sont différents pour toutes les études mentionnées, des généralités peuvent néanmoins être tirées. Les chocs de santé ont, en générale, des impacts négatifs sur les décisions

[9]Ces pays étant l'Autriche, la Belgique, le Danemark, la France, l'Allemagne, la Grèce, l'Italie, les Pays-Bas, l'Espagne, la Suède et la Suisse.

sur le marché du travail et sur la richesse. Ils ont néanmoins des effets plus contrastés sur la santé.

5. Contributions

La question de recherche à laquelle vise la thèse est la suivante : “Est-ce que l'expérience du système de santé a induit un changement des préférences ou des traits de personnalité de l'individu ?”

Pour répondre à cette question, nous étudierons l'impact de divers événements de santé sur la perception du contrôle (chapitre 1) et sur la tolérance au risque (chapitre 2). Les résultats à ces questions orientent les questions soulevées dans les chapitres suivants. Si les traits et les préférences sont des paramètres stables, alors se pose la question de savoir s'ils sont déterminés bien avant la naissance de l'individu, *in-utero*. Pour ce faire, nous allons étudier si le niveau de testostérone reçu pendant la grossesse permet d'expliquer le niveau actuel de tolérance au risque (chapitre 3). Si, à l'inverse, les traits et les préférences sont des paramètres instables nous étudierons si cette instabilité peut expliquer pourquoi les individus ont, en moyenne, de meilleurs comportements de santé suite à un choc de santé (chapitre 4).

Documenter si les traits de personnalité ou les préférences économiques sont des paramètres stables peut intéresser à la fois le décideur public et les chercheurs en sciences sociales.

Déterminer que les traits et les préférences se modifient en fonction du vécu de l'individu peut avoir des conséquences significatives au niveau macroéconomique. En effet, comme mentionné dans la section 2 de cette introduction, les traits et préférences influencent bons nombres de comportements des individus. Ainsi, plus un pays va recenser des habitants ayant, par exemple, une faible tolérance au risque, plus ce pays va connaître des taux d'auto-entreprenariats faibles, mais des niveaux d'épargnes forts. Le niveau d'emploi et d'épargne étant des composantes majeures de la croissance économique, des changements dans la tolérance au risque peuvent conduire à des changements macroéconomiques importants. Connaître les déterminant de ces changements peut intéresser le décideur public désireux d'anticiper d'éventuelles fluctuations des performances macroéconomiques.

La prise en compte de déterminants comportementaux dans la prise de décision est, par ailleurs, en lien avec la volonté de plusieurs gouvernements de l'OCDE. Ceci est notamment le cas du gouvernement français qui a lancé en 2018 la création de trois départements au sein de la Direction Interministérielle de la Transformation Publique, dont un portant spécifiquement sur les "méthodes innovantes, sciences comportementales et écoutes usagers".

Les chercheurs en sciences sociales pourront aussi être intéressés par les résultats de cette thèse. En premier lieu, les chercheurs en économie empirique. En effet, documenter l'instabilité des préférences et des traits implique que les méthodes à effet-fixes ou les estimations en première différence ne prendront pas en compte les variations de ces paramètres. Par ailleurs, le raisonnement de l'économiste s'articule autour de la mise en évidence de relations causales – ou de s'en approcher – le distinguant ainsi des autres spécialistes des sciences sociales. Ceci constitue donc un avantage comparatif dans la méthodologie adoptée par la discipline (Bénassy-Quéré et al. (2017)). Ce faisant les résultats produits dans cette thèse pourront, peut-être, intéresser les disciplines proches des thèmes étudiés ici, comme par exemple la psychologie sociale de la santé, la psychologie de la personnalité ou la psychologie positive.

Les sous-parties suivantes détaillent les contributions de chaque chapitre.

5.1. Chapitre 1

La littérature empirique portant sur le lien entre traits de personnalité et événements de santé montrent des résultats mitigés. Les traits de personnalité ne vont pas être sensibles à tous ces événements. Néanmoins, quelque soit le choc considéré, les variations sont modestes mais significatives[10].

Nous contribuons à cette littérature de quatre manières. D'abord, en proposant l'impact de long terme (i.e. 10 ans) d'un choc de santé sur la perception du contrôle, l'état de l'art n'a montré que des impacts de court (1 ou 2 ans) ou de moyen terme (4 ou 5 ans). Ensuite, en catégorisant ce choc de santé de deux manières : en fonction de sa chronicité (mesurée par le nombre d'hospitalisations) et de sa sévérité (mesurée par la durée de l'hospitalisation). Puis, en étudiant un échantillon allemand car les autres études portent principalement sur des échantillons australiens. La perception du contrôle étant corrélée avec les dimensions

[10] Le lecteur intéressé par les détails des résultats trouvés en fonction des chocs étudiés peut se référer à l'introduction du chapitre 1.

culturelles, prendre en compte d'éventuelle différence entre les pays est important. Enfin, en montrant que la perception du contrôle se modifie suite à des événements importants de santé, alors les modèles à effets fixes ou les méthodes de première différence, ne permettent pas de contrôler pour ces variables (longtemps supposées invariables, donc éliminées par ces méthodes).

Nous utilisons la base de données de panel allemande : G-SOEP. Elle est représentative de la population allemande et inclut des individus âgés de plus de 16 ans et propose un large éventail de données de santé, de travail, d'éducation, ou de traits de personnalité. Elles nous permet de contrôler pour un grand de variables comme l'âge, le niveau d'éducation, le revenu, le sexe, le lieu de vie, la situation professionnelle, la situation familiale, le nombre d'hospitalisation, le nombre de nuit passée à l'hôpital, le niveau de santé auto-reporté et par le fait d'avoir une assurance privée.

Pour prendre en compte le caractère non-aléatoire du choc de santé (ici une hospitalisation), nous utilisons un modèle à effets-fixes. La perception du contrôle des individus ayant subi un tel choc (groupe de traitement) est comparée, toutes choses égales par ailleurs, avec n'ayant jamais du choc (groupe de contrôle).

Les résultats montrent que les individus ayant subi un choc de santé vont réduire légèrement mais significativement leur perception du contrôle. Plus précisément, ils réduisent de 0.007 ($p=0.001$) leur LOC. Ce déclin est attribuable aux individus qui avaient, avant l'hospitalisation, déjà une perception faible de leur contrôle sur les événements de leur vie. De plus, les individus qui ont des hospitalisations plus graves ou plus longues ont des déclins plus importants. L'effet du choc est également hétérogène en fonction de l'âge : les individus les plus jeunes sont plus à mêmes à modifier leur perception du contrôle que les plus âgés. Ces résultats sont, par ailleurs, robustes. Ceci montre que les traits de personnalité peuvent se modifier légèrement suite à des événements de santé importants.

5.2. Chapitre 2

Ce chapitre propose d'analyser la stabilité des attitudes et des préférences vis-à-vis du risque suite à un événement important de santé. Ce faisant il s'inscrit dans une littérature qui se développe, mais dont les résultats sont encore hétérogènes (développé plus en détail dans la section revue de la littérature du chapitre 2).

Notre étude s'inscrit dans cette littérature et y contribue en analysant l'impact d'un choc de santé à la fois sur les attitudes et les préférences vis-à-vis du risque. Les attitudes vis-à-vis du risque sont mesurées en utilisant trois questions dans lesquelles les individus auto-reportent leur disposition à prendre des risques en général, en santé et en finance. Les individus doivent classer leur réponse sur une échelle allant de 0 (pas du enclin à prendre des risques) à 10 (très enclin à prendre des risques). Les préférences vis-à-vis du risque sont mesurées en utilisant deux jeux loteries incitées de HL et de B-EG. Nous considérons deux chocs de santé : les chocs chroniques (diabètes, dépression et épilepsie) et les chocs aigues (problèmes cardiaques et cancers). De plus, nous sommes les premiers à étudier l'impact de ces chocs sur un échantillon représentatif de la population anglaise.

Pour mener à bien cette étude, nous utilisons des données de panel provenant de l'*Innovative Panel du UK Household Longitudinal Study.* Les données de l'IP permettent d'avoir des informations sur la tolérance au risque (mesurée par les préférences et les attitudes vis-à-vis du risque) et sur les préférences vis-à-vis du temps. Elles sont après appariées avec les données du questionnaire général de l'UKHLS. L'IP est un échantillon représentatif de la population l'Angleterre, de l'Ecosse, et du pays de Galles, mais exclu l'Irlande. À l'inclusion, 40 000 ménages ont répondu au questionnaire général. Chaque année, les répondants sont invités à répondre au même questionnaire pour y notifier les changements les concernant. Les individus ayant 16 ans ou plus peuvent répondre à ce questionnaire, les plus jeunes doivent, quant à eux, remplir un autre questionnaire.

Pour mesurer l'impact de ces chocs sur les attitudes et des préférences vis-à-vis du risque, nous utilisons un appariement par score de propension. Cet appariement est fait avec des variables invariables dans le temps ce qui permet de contourner le problème que l'on observe la tolérance au risque des individus qu'après le choc de santé. Plus précisément, notre appariement se fait sur les variables suivantes : le niveau d'éducation de l'individu, son année de naissance, son sexe, sur la nationalité de son père et de sa mère, ainsi que sur la situation en emploi de ces derniers. Les individus ayant subi un choc de santé sont dans le groupe de traitement, ceux n'en ayant pas subi sont dans le groupe de contrôle.

Les résultats montrent qu'il n'y a aucun effet d'un choc de santé sur les attitudes et les préférences vis-à-vis du risque. L'unique exception est l'attitude vis-à-vis du risque en général qui est, faiblement mais positivement, associé avec le choc de santé. Ce résultat peut s'expliquer par le fait que les préférences et les attitudes couvrent des dimensions et des aspects différents de la tolérance au risque des individus (Crosetto and Filippin (2016); Galizzi et al. (2016a); Brañas-Garza et al. (2018)).

5.3. Chapitre 3

La formation des préférences semble donc ne pas être en lien avec des événements de santé. Des facteurs biologiques entrent-ils alors en compte dans la formation des ces préférences ?

Pour répondre à cette question, nous allons étudier si l'exposition à la testostérone reçue par le fœtus *in-utero* est un déterminant de la tolérance au risque à l'âge adulte. Pour ce faire, nous utilisons l'index de Manning. Cet index est défini comme le ratio de la longueur de l'index sur la longueur de l'annulaire. Il a été montré que les doigts ont de récepteurs aux hormones stéroïdiennes que leurs tailles dépendent de l'exposition à la testostérone reçu pendant la grossesse (Manning et al. (1998); Manning et al. (2014)). De plus la testostérone stimule la croissance de l'index par rapport à la taille des autres doigts (Manning et al. (2002); Lutchmaya et al. (2004)). Ainsi, le ratio de l'index sur l'annuaire plus petit pour les hommes qui ont reçu plus de testostérone que les femmes.

Ce faisant notre étude vise à documenter si les différences dans la tolérance au risque entre les hommes et les femmes est déterminée avant leur naissance. En d'autres termes, est-ce que la relative aversion au risque qu'ont, en moyenne, les femmes par rapport aux hommes (e.g. Byrnes et al. (1999); Croson and Gneezy (2009)) est déterminée avant les facteurs les facteurs culturelles ?

Les données utilisées sont les mêmes que celles du chapitre 2 à savoir celles provenant de l'*Innovative Panel du UK Household Longitudinal Study* que nous ne représenteront pas ici.

En utilisant des modèles Probit et des régressions linéaires classiques, nous montrons que l'indice de Manning n'est pas significativement associé à la tolérance au risque et aux préférences temporelles. En d'autres termes, il semble donc que les préférences économiques ne soient pas déterminées *in-utero*.

5.4. Chapitre 4

La littérature empirique a montré qu'il existe une certaine homogénéité des effets de différents chocs de santé sur les comportements de santé des individus. Les individus ayant subi de tels chocs, quelque qu'en soit leur nature, adoptent des meilleurs comportements de santé. Par ailleurs, si ce choc ne les touche pas directement (i.e. si le choc est subi par un individu de leur entourage), leur comportement de santé ne sont pas impactés[11].

Nous contribuons à cette littérature de trois manières. D'abord, en proposant un nouveau choc de santé : les accidents de la route ou du travail ayant entraîné un recours aux soins. Ce type de choc n'a pas été investigué précédemment car il n'est pas la conséquence directe des comportements de santé, comme l'est un cancer du poumon ou une maladie cardio-vasculaire. Toutefois, ces accidents sont probablement moins sujets au biais de causalité inverse que ne l'est le cancer du poumon. Ensuite, en utilisant un échantillon de travailleur français, nous étudions les effets de choc de santé sur une population non étudiée jusqu'à présent. Enfin, en étendant la gamme des comportements de santé analysés précédemment : la consommation totale de tabac (nombre de cigarettes, mais aussi de pipes, cigares et cigarillos), d'alcool et l'IMC. Ce faisant, nous pouvons également analyser d'éventuels effets de report non documentés précédemment : un individu subissant un choc de santé peut certes consommer moins de tabac, mais augmenter sa consommation d'alcool.

Pour ce faire, l'étude a été conduite à partir de la cohorte Gazel. Cette cohorte a suivi 20 000 volontaires, agents et anciens agents d'Electricité de France (EDF) et du Gaz de France (GDF), pendant 25 ans (1989-2014). Les participants, âgés de 35 à 50 ans en 1989, font l'objet d'un suivi complet au cours duquel différentes données sont recueillies : modes de vie, carrières professionnelles, expositions professionnelles, recours aux soins et banque de matériel biologique. Le taux d'attrition est très bas avec 201 sujets perdus sur les 18 premières années, soit environ 0,9 % de l'échantillon et seuls 3,1 % des participants n'ont jamais renvoyé leur questionnaire après avoir participé en 1989[12]. Par ailleurs, l'exploitation du caractère longitudinal des données permettait de bien saisir l'évolution des comportements de santé.

Les données permettent de comparer les consommations d'alcool, de tabac et l'IMC

[11] Le lecteur par cette littérature pourra se référer à la section correspondante dans le chapitre 3.

[12] Pour plus d'information sur la cohorte Gazel, le lecteur pourra consulter le site de la cohorte (ici) ainsi que Goldberg et al. (2006).

des individus ayant subi un choc de santé ("groupe de traitement"), avec celles d'un autre groupe n'ayant pas subi ce choc ("groupe de contrôle"). Or, le choc de santé n'étant pas aléatoire, les personnes des deux groupes ont des caractéristiques différentes. Dans le groupe de traitement, les individus sont notamment plus âgés et ont un niveau de revenu plus faible que les personnes du groupe de contrôle. Pour corriger, en partie, ces différences initiales entre les groupes, et donc pour s'assurer d'une meilleure comparabilité, nous utiliserons un modèle à effets fixes. Pour contrôler de la robustesse de nos résultats, nous utiliserons différentes autres méthodes d'identification en combinant une différence-en-différences (DiD) avec des appariements par score de propension (SP), par radius et par kernel.

Les résultats montrent qu'un choc de santé induit une baisse significative et durable de la consommation de tabac et d'alcool pendant, respectivement, 5 ans et pendant 3 ans, mais n'influence pas l'IMC. Les individus subissant un tel choc fument en moyenne deux cigarettes de moins par semaine que ceux ne subissant pas ce choc. Par ailleurs, cette baisse est différenciée : les gros fumeurs diminuent davantage leur consommation que les petits fumeurs. L'effet du choc impacte également la consommation d'alcool : 0,05 verres d'alcool de moins par semaine. Au-delà des horizons temporels mentionnés, les deux groupes retrouvent des consommations identiques. Cette recherche vient donc confirmer sur plusieurs aspects les travaux antérieurs : un choc de santé peut conduire à une amélioration des comportements de santé. Ces résultats sont à mettre en exergue avec ceux des tentatives d'arrêt ou de diminution de la consommation de tabac. Ces tentatives durent, en moyenne, 2,4 mois (e.g. Segan et al. (2006); Herd et al. (2009)). Ce qui est 25 fois moins long que la diminution trouvée suite à un choc de santé. Ainsi, nos résultats montrent que subir un choc de santé est un déterminant majeur de la durée de réduction de la consommation de tabac[13].

6. Conclusion

Pour limiter l'incidence croissante des maladies chroniques, un grand nombre de pays de l'OCDE ont mis en place des politiques de prévention et d'information axées sur les changements de comportement de santé. En effet, améliorer les comportements de santé

[13] Comme le sont l'âge, la présence d'une maladie due au tabac, la sensation de maladie (Hughes et al. (2004); Meyer et al. (2003); Godtfredsen et al. (2001).

pourrait, en partie, réduire le nombre de décès liés à l'obésité, à la consommation de tabac et d'alcool.

Un premier type d'intervention visait à procurer de l'information en ciblant (de l'anglais, *targeting policy*) une catégorie spécifique de la population (e.g. les moins riches, les moins éduqués). D'autres types d'interventions visaient à prendre en considération les perceptions et les croyances de l'individu dans le contenu informationnel (de l'anglais, *tailoring policy*).

La plupart de ces deux interventions étaient donc principalement basées sur des différences inter-individuelles. Néanmoins, au-delà de ces différences, les variations intra-individuelles sont probablement aussi à considérer lors de l'élaboration de politiques publiques. En effet, pourquoi un homme ayant décidé d'aller faire un diagnostic d'un cancer de la prostate, refuse d'aller au second rendez-vous ? Pourquoi une femme qui est allé faire un dépistage du cancer du sein, va être plus à même de faire d'autres dépistages ? L'expérience du système de santé a-t-elle induit un changement de préférence ou de trait de personnalité de l'individu ?

Tout le but de cette thèse est d'y répondre en quatre chapitres. Les résultats du premier chapitre montrent que les individus ayant subi un choc de santé vont réduire, sensiblement, mais significativement leur perception du contrôle. Cette baisse est d'autant plus grande que l'individu avait, avant ce choc, une plus grande perception du contrôle. Les individus vont donc d'avantage considérer que ce qui leur arrive à dû à des événements extérieurs plutôt qu'à leurs propres actions. Les résultats du second chapitre indiquent que la tolérance au risque est, quant à elle, inchangée suite à un choc de santé. Ceci est robuste quelque soit la méthode utilisée pour mesurer le risque (expérimentale ou auto-évaluée).

La formation des préférences semble donc ne pas être en lien avec des événements de santé. Des facteurs biologiques entrent-ils alors dans la formation des préférences ? Les résultats du troisième chapitre semblent indiquer que non. Plus précisément, le niveau de testostérone reçu pendant la gestation n'a pas d'influence sur les comportements actuels vis-à-vis du risque et du temps. En utilisant l'indice de Manning – marqueur biologique d'exposition à la testostérone *in-utero* - nous montrons qu'il n'est pas corrélé avec les attitudes et les préférences actuelles vis-à-vis du risque et du temps. Par ailleurs, bien que les chocs de santé n'aient pas modifié la tolérance au risque, ils ont provoqué des changements significatifs de comportement de santé. Les résultats du dernier chapitre montrent qu'un choc de santé induit une baisse significative et durable de la consommation de tabac et d'alcool pendant, respectivement, 5 ans et pendant 3 ans. Les individus subissant un tel choc fument en moyenne deux cigarettes de moins par semaine que ceux ne subissant pas ce choc. Par ailleurs, cette baisse est différenciée : les gros fumeurs diminuent davantage leur consommation que les petits fumeurs. Ces résultats sont à mettre en exergue avec ceux des tentatives d'arrêt ou de diminution de la consommation de tabac. Ces tentatives durent, en moyenne, 2,4 mois (e.g. Segan et al. (2006); Herd et al. (2009)). Ce qui est 25 fois moins long que la diminution trouvée suite à un choc de santé. Ainsi, nos résultats montrent que subir un choc de santé est un déterminant majeur de la durée de réduction de la consommation de tabac.

Les résultats de ces chapitres pourraient être utilisés afin affiner les interventions de santé publique existantes. Pourrait être testé, par exemple, une intervention combinant contenu informationnel personnalisé et approche narrative (i.e. transmettre l'expérience du vécu d'un trouble de santé). En effet, ces deux stratégies reprennent trois des résultats des travaux de cette thèse. Premièrement, les individus sont sensibles à l'expérience personnelle qu'ils ont du système de santé (puissent qu'ils modifient leurs comportements suite à un choc de santé – résultats du chapitre 4). Deuxièmement, suite à ces chocs, ils modifient davantage leur perception du contrôle que leur tolérance au risque (résultats des chapitres 1 et 2). De plus, ces deux types d'interventions se sont montrées efficaces pour modifier significativement et durablement la discrimination à l'égard des personnes musulmanes et des personnes transgenres (Broockman and Kalla (2016); Tusicisny (2017)). Ces interventions étaient basées sur la capacité à éprouver de la réciprocité (de l'anglais, *perspective-taking*) avec ces deux groupes d'individus.

Des problématiques adjacentes à celles développées dans cette thèse pourraient faire l'objet de travaux ultérieurs.

D'abord, en étendant les résultats du chapitre deux au cas français. Ceci permettrait de documenter les effets d'un événement de santé sur les préférences et les attitudes vis-à-vis du risque et du temps chez des sujets français. Mais aussi en identifiant quels types d'événements de santé impacteraient le plus de tels paramètres. Par exemple, est-ce qu'un cancer modifie davantage qu'un accident vasculaire cérébral la tolérance vis-à-vis du risque ? Est-ce qu'un événement dépressif modifie plus longtemps l'impatience qu'un diabète ? Apparier un module comportemental, contenant des questions sur les préférences économiques, avec la base de données Constances, pourrait apporter quelques réponses à ces réponses.

Enfin, en analysant si un événement de santé ayant altéré la santé physique d'un individu va provoquer une maladie mentale ou aggraver une existante. Ceci pourrait être fait en utilisant un échantillon de personnes âgées, plus sensibles aux maladies mentales et dont l'évolution démographique justifie l'intérêt. Pour ce faire une étude utilisant les données *SHARE* pourrait faire l'objet d'un futur agenda de recherche.

⋆ ⋆ ⋆ ⋆ ⋆

Le reste de la thèse est rédigé en anglais.

General Introduction

Contents of the General Introduction

1. Definition of non-cognitive skills

There are many determinants of health that can impact an individual, including access to quality medical care, environmental conditions, or genetic factors. However, in high-income countries where the chronic disease incidence rate has increased, health behaviors are particularly important. In 2018, the World Health Organization (WHO) estimated that chronic diseases caused 88% of deaths in high-income countries (WHO (2018)). Cardiovascular diseases are responsible for most chronic disease deaths (17.9 millions), followed by cancers (9 millions), respiratory diseases (4 millions), and diabetes (1.6 millions). Tobacco and alcohol use, sedentary lifestyles, and unhealthy diets are overall health behaviors that increase the risk of developing such chronic diseases.

Therefore, health behavior change is an opportunity to reduce the burden of chronic diseases. Promoting such change is, however, a complex issue as health behaviors have many dimensions. By far, the two most important dimensions are educational attainment and income: highly educated individuals and high-income earners adopt healthier behaviors (e.g. Cutler and Lleras-Muney (2010); Conti et al. (2010))[14]. Additionally, the quality of parenting, gender, place of residence, social networks, and culture are also associated with health behaviors (e.g. Currie (2009); Lundborg and Andersson (2008); Schünemann et al. (2017)).

Beyond such socio-economic characteristics, the adoption of healthier behaviors can also be explained by differences in non-cognitive skills, such as inter-individual differences in personality traits (e.g. openness to experience, conscientiousness, perception of control, self-esteem) and economic preferences (i.e. time, risk and social preferences).

1.1. Personality traits

Personality traits are defined by personality psychologists as "the relatively enduring patterns of thoughts, feelings, and behaviors that reflect the tendency to respond in certain ways under certain circumstances" (Roberts (2007, 2009), p.2). The most widely accepted

[14] Contoyannis and Jones (2004); Balia and Jones (2008) show contradicting findings. Once accounting for endogeneity in behavioral choices, the size of socio-economic effects is reduced.

taxonomy of personality traits is the Big-Five or the five-factor model (Goldberg (1992))[15]. It originates from the 1936 Allport and Odbert (1936)'s lexical hypothesis positing that the most important individual differences are encoded in language. The authors combed English dictionaries and found 17,953 personality-describing words, which were later reduced to 4,504 personality-describing adjectives. Subsequently, several personality psychologists working on different samples concluded that personality traits could be organized into five dimensions. These five dimensions have been designated as the "Big-Five".

The Big-Five contains the following dimensions: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. Each dimension summarizes a larger number of distinct and more specific personality characteristics. They are called "facets" by John (1990) and Costa and McCrae (1992a). Table 1 presents and defines these five dimensions and summarizes the 30 lower-level facets (six facets for each of the five dimensions)[16]. To measure each of these dimensions, individuals have to self-report the degree to which each of these five dimensions describes them[17].

Another important concept in psychology is the locus of control (LOC) originated from Rotter (1954, 1966). It represents the framework of the social learning theory of personality (see Almlund et al. (2011) for a review) and refers to the extent to which individuals believe they have control over events. More specifically this concept captures "a generalized attitude, belief or expectancy regarding the nature of the causal relationship between one's own behaviors and its consequences" (Rotter (1966), p.2). A distinction is typically made between internal and external LOC. Individuals with an internal LOC see future outcomes as being contingent upon their own behaviors. Those with an external LOC believe that future outcomes are, to a large extent, beyond their control. Thus, individuals with an internal LOC believe their outcomes are primarily determined by their own actions, including their personal level of effort or investment, as well as their own mistakes and failures. Conversely, individuals with an external LOC believe that factors such as luck, chance, fate, destiny, or the actions of others play a larger role in determining their outcomes.

Such perception of control is measured using the Rotter scale, which contains ten ques-

[15]See John and Srivastava (1999) for an historical overview of the development of the Big-Five, and and Costa and McCrae (1992a) and Digman (1990) for a review of the emergence of this concept.

[16]See more details on Borghans et al. (2008) and Almlund et al. (2011).

[17]Such is traditionally done with a scale ranging from 1 ("not at all") to 7 ("very well").

tions. Individuals must indicate whether they agree with these 10 statements[18]. There are two sets of questions: those that are internal questions, and those that are external ones.

Table 1: Big-Five indicator

Big-Five indicator	American Psychology Association Dictionary	Facets
Extroversion	An orientation of one's interests and energies toward the outer world of people and things rather than the inner world of subjective experience; characterized by positive affect and sociability.	Warmth, Gregariousness, Assertiveness, Activity, Excitement seeking, Positive emotions.
Agreeableness	The tendency to act in a cooperative, unselfish manner	Trust, Straightforwardness, Altruism, Compliance, Modesty, Tender-mindedness.
Conscientiousness	The tendency to be organized, responsible, and hardworking.	Competence, Order, Dutifulness, Achievement striving, Self-discipline, Deliberation
Neuroticism	A chronic level of emotional instability and proneness to psychological distress/Predictability and consistency in emotional reactions, with absence of rapid mood change.	Anxiety, Angry hostility, Depression, Self-consciousness, Impulsiveness, Vulnerability
Openness to experience	The tendency to be open to new aesthetic, cultural, or intellectual experiences.	Fantasy, Aesthetics, Feelings, Actions, Ideas, Values

Source: Costa and McCrae (1992b); Hogan et al. (2007); and Borghans et al. (2008).

[18]Such is traditionally done with a scale ranging from 1 ("I do not agree at all") to 7 ("I fully agree").

More precisely, questions 1, 6, and 9 load onto an internal factor, and 2, 3, 4, 5, 7, 8 and 10 load onto an external factor. The different components of this scale are summarized in Table 2. It is worth noticing that these PhD chapters will only focus on LOC as a measure of personality traits.

Table 2: Locus of control scale

Internal questions	Q1. My life course depends on me Q6. Success takes hard work Q9. Abilities are more important than effort
External questions	Q2. Haven't achieved what I deserve Q3. What you achieved depends on luck Q4. Influence on social conditions through involvement Q5. Other make crucial decisions in my life Q7. Doubt my abilities when problems arise Q8. Possibilities are defined by social conditions Q10. Little control over my life

Source: Rotter (1954, 1966); Borghans et al. (2008); and Almlund et al. (2011).

1.2. Economic preferences

Economic preferences refer to the following parameters: risk, time and social preferences. Risk preferences, in the standard expected utility framework, refers to the willingness to take risk and is captured by the curvature of this utility function Gollier (2001)). Time preference describes how an individual trades off utility at different points in time (e.g. Samuelson (1937); Frederick and Loewenstein (2002)). Social preferences capture the fact that an individuals' utility does not depend only on his or her payoffs, but also by others' behaviors. It includes, for example, altruism (e.g. Eckel and Grossman (1996)), and negative and positive reciprocity (e.g. Falk and Fischbacher (2006)). This PhD dissertation will only focus on the first two aspects - risk and time preferences - and not social preferences.

Risk tolerance is the degree of variability in investment returns an individual is willing to withstand. Two approaches prevail to measure risk tolerance: self-reports and incentivized experiments[19]. The former measures risk attitudes, and the latter measures risk preferences. A prototypical example of risk attitude measurement is the corresponding question: "How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?"[20] This PhD dissertation focuses on three self-reported questions, developed by Dohmen et al. (2011), on willingness to take risks in general, in health, and in finance. We also use some of the most widely-cited experimental approaches to measure risk preferences encompassed by Holt and Laury (2002) price list approach, and Binswanger (1980), and Eckel and Grossman (2002) choice between different gambles. In these experiments, individuals typically choose between different two-outcome lotteries in which higher expected payoffs come at the cost of a higher variance of payoff (i.e. riskier).

For Holt and Laury (2002)'s measure of risk preferences, subjects responded to two multiple price list (MPL) binary lotteries tasks. One has low monetary stakes (HL low) and the other, high monetary stakes (HL high). Each task consisted of a series of nine binary questions, where subjects had to choose between two risky lotteries, lottery A or lottery B. Lottery B was "riskier" than lottery A, in the sense that its two possible monetary outcomes were more spread apart from each other, with one very high monetary prize, but also with one very low prize, each occurring with different probabilities. The series of questions varied the probabilities of winning the high prize payment in the two lotteries. Typically, subjects prefer lottery A with low probabilities of a high prize payment, but then "switch" to preferring lottery B when such a probability is sufficiently high. The point in the series of questions where a respondent switches from preferring lottery A to preferring lottery B can be used to infer their risk aversion. In particular, under standard assumptions of Expected Utility Theory (EUT) (e.g. Hey and Orme (1994); Mongin (1997); Harrison and Rutstrom (2009)) and Constant Relative Risk Aversion (CRRA) (e.g. Dyer and Sarin (1982); Meyer and Meyer (2005); Chiappori and Paiella (2011)), one can associate a range of values of risk aversion to each question in which the respondent switches from preferring lottery A to lottery B (see

[19] A third approach infers willingness to take risks from field behaviors such as investment decisions. Such measures, however, do not only measure risk tolerance but also opportunities to engage in a given behaviors, and therefore will not be used in this PhD dissertation.

[20] The answer is ranked from 0 ("I am a person unwilling to take risks") to 10 ("I am a person fully prepared to take risks").

more in Table 3).

Table 3: HL lottery probabilities, payoffs, expected values, and corresponding CRRA ranges

HL Low

Lottery A				Lottery B				CRRA Range	
P	GBP	(1-p)	GBP	P	GBP	(1-p)	GBP	Lower bound	Upper bound
0.1	40	0.9	32	0.1	77	0.9	2	$-\infty$	-1.71
0.2	40	0.8	32	0.2	77	0.8	2	-1.71	-0.95
0.3	40	0.7	32	0.3	77	0.7	2	-0.95	-0.49
0.4	40	0.6	32	0.4	77	0.6	2	-0.49	-0.14
0.5	40	0.5	32	0.5	77	0.5	2	-0.14	0.15
0.6	40	0.4	32	0.6	77	0.4	2	0.15	0.41
0.7	40	0.3	32	0.7	77	0.3	2	0.41	0.68
0.8	40	0.2	32	0.8	77	0.2	2	0.68	0.97
0.9	40	0.1	32	0.9	77	0.1	2	0.97	1.37

HL High

Lottery A				Lottery B				CRRA Range	
P	GBP	(1-p)	GBP	P	GBP	(1-p)	GBP	Lower bound	Upper bound
0.1	100	0.9	40	0.1	180	0.9	2	$-\infty$	-0.75
0.2	100	0.8	40	0.2	180	0.8	2	-0.75	-0.32
0.3	100	0.7	40	0.3	180	0.7	2	-0.32	-0.05
0.4	100	0.6	40	0.4	180	0.6	2	-0.05	0.16
0.5	100	0.5	40	0.5	180	0.5	2	0.16	0.34
0.6	100	0.4	40	0.6	180	0.4	2	0.34	0.52
0.7	100	0.3	40	0.7	180	0.3	2	0.52	0.70
0.8	100	0.2	40	0.8	180	0.2	2	0.70	0.91
0.9	100	0.1	40	0.9	180	0.1	2	0.91	1.20

For Binswanger (1980); Binswanger et al. (1981); and Eckel and Grossman (2008a) (B-EG) measurement of risk preferences asked subjects to choose among six lotteries with a 50% chance of receiving either a low or a high monetary prize. One lottery was a safe bet (lottery A, with a variance of 0), whereas the other five lotteries entailed increasing levels of variance, and thus, of risk. Under standard EUT and CRRA assumptions, the choice of each lottery can be associated with a corresponding range of risk aversion (see more in Table 4).

Table 4: B-EG lottery probabilities, payoffs, expected values, and corresponding CRRA ranges

Choice	Payoff				CRRA Ranges	
	Low	High	Expected return	Standard deviation	Lower bound	Upper bound
A	28	28	28	0	3.36	$+\infty$
B	24	36	30	8.5	1.16	3.46
C	20	44	32	17	0.71	1.16
D	16	52	34	25.5	0.499	0.71
E	12	60	36	33.9	0	0.499
F	2	70	36	48.1	$-\infty$	0

Time preferences are typically measured through individual discount rates (IDR). These IDR were introduced by Coller and Williams (1999) and expanded by Harrison et al. (2002). Individuals must choose between different Smaller Sooner (SS) and Larger Later (LL) options to measure their time preferences using incentive-compatible experimental tests. In this PhD dissertation, the same set of inter-temporal binary options was presented twice, one with Front End Delay (FED) and one without. In both FED and non-FED cases, questions were presented in blocks ordered according to three increasing time horizons occurring between the SS and the LL option: 1 month, 3 months, and 12 months.

Within the FED block, a first sub-block of questions presented a choice between an SS Option A involving a "principal" payment of £100 in one month, and an LL Option B with 1-month intervals involving a larger monetary amount after two months. The 12 questions in the sub-block were constructed in a way that the LL option had annual implicit interest rates equal to 5%, 10%, 15%, 20%, 25%, 30%, 40%, 50%, 60%, 80%, 100%, and 150%. Amounts for the LL monetary values were calculated using simple, rather than compounded (e.g. bi-annually, quarterly), annualized discounting rates. The second sub-block of FED questions used the same annual implicit discount rates but with 3-month time horizons (one month in Option A versus four months in Option B), while the third sub-block of FED questions used the same discount rates for a time interval of 12 months (one month in Option A versus 13 months in Option B). The non-FED block of 36 questions followed with the same 1-month, 3-month, and 12-month intervals, and the same implicit discount rates, but no FED. The wording of the questions was the same throughout: "Between Option A and Option B, which option do you prefer? Option A: receiving £100 in one month; Option B: Receiving £100.42 in two months." A typical sample of questions is reported in Table 5 below.

Table 5: FED 1 block of questions on time discounting

Option A (in 1 month)	Option B (in 2 months)	Which option do you prefer?	
£100	£100.42	A	B
£100	£100.83	A	B
£100	£101.25	A	B
£100	£101.67	A	B
£100	£102.08	A	B
£100	£102.50	A	B
£100	£103.33	A	B
£100	£104.17	A	B
£100	£105.00	A	B
£100	£106.67	A	B
£100	£108.33	A	B
£100	£112.50	A	B

1.3. Complementary but distinct parameters

Throughout this PhD dissertation I follow Heckman and Kautz (2012) (p.2) and Kautz et al. (2014) (p.2, p.7) who group traits and preferences as non-cognitive skills. The authors state, "personality traits, goals, motivations and preferences are character skills or non-cognitive skills." Furthermore, they explain that as non-cognitive skills can be shaped and changed over the life cycle (see more evidence in section 3 of the General Introduction), they are rightly defined as "skills." Other empirical economics have followed such categorization (e.g. Kuhn and Weinberger (2005); Cobb-Clark and Schurer (2013), Elkins et al. (2017)).

Economic preferences and personality traits have been shown to be complementary but distinct parameters (Becker et al. (2012)). Almlund et al. (2011) provide first evidence on the associations between economic preferences and personality measures through an intuitive mapping. They report that time preferences are likely to be related to conscientiousness, self-control, and consideration of future consequences; while risk tolerance is likely to be related to openness to experience, and impulsive sensation-seeking. Despite this intuitive mapping of preferences to traits, the empirical evidence of such mapping is weak and mixed.

Concerning the association between time preferences and personality traits, Daly et al. (2009) find a negative correlation between financial discount rates and self-control, conscientiousness, consideration for future consequences, and affective mindfulness. Such findings are based on an experiment using a sample of Dublin college students performing experimental monetary tasks[21] and psychometric tests[22]. However, Dohmen et al. (2011) do not corroborate this negative correlation. They find that none of the Big-Five traits are correlated to time discounting, based on an experiment in a representative sample of the German adult population. Finally, Anderson et al. (2012) find a positive correlation between agreeableness and time discounting based on an experiment in a sample of truck driver trainees.

Concerning the association between risk tolerance and personality traits, Dohmen et al. (2011) find a negative correlation between risk aversion and openness to experience and agreeableness. Additionally, Hirsh and Inzlicht (2008) and Rustichini et al. (2016) find that risk attitudes are negatively correlated with neuroticism and conscientiousness. In contrast, Bibby and Ferguson (2011) and Borghans et al. (2008) find a positive correlation between risk aversion and neuroticism and agreeableness, but a negative correlation with ambition. Similarly, Anderson et al. (2012) find that neuroticism is positively correlated with risk aversion, but only for lotteries over gains, not losses. Finally, Eckel and Grossman (2002) find no association between risk aversion and sensation seeking.

In sum, although many measures of personality and preferences seem conceptually re-

[21] The measure of financial discounting is a monetary task based on Kirby et al. (1999) in which respondents were offered a fixed set of 27 binary choices between smaller immediate rewards and delayed rewards.

[22] This includes the Big-Five indicator, and a self-control scale.

lated, the empirical associations are not uniform across studies; often, measures of preferences are uncorrelated with similar personality traits. Nevertheless, in several studies, neuroticism is associated with risk aversion, and conscientiousness is associated with delay acceptance.

Such empirical results are based on model predictions, where it is worth exploring how traits and preferences enter economic models. To provide a framework of analysis we follow Cunha et al. (2010); Almlund et al. (2011); and Heckman and Kautz (2012). They state that the production of a health outcome for an individual i at time t is a function of resources (e.g. income, educational attainment, parenting quality), R_i, personality traits, P_i, external factors (e.g. genetics, health care access), E_i, and effort, e_i, allocated to the production of this outcome. This could be formally written in equation 1:

$$H_{i,t} = \phi_{i,t}(R_{i,t}, P_{i,t}, E_{i,t}, e_{i,t}) \tag{1}$$

Effort allocated to the production of this outcome is also a function of resources, personality traits, external factors, and preferences ($\epsilon_{i,t}$). This could be formally written in equation 2:

$$e_{i,t} = \gamma_{i,t}(R_{i,t}, P_{i,t}, E_{i,t}, \epsilon_{i,t}) \tag{2}$$

These two equations also formalize the difficulty in establishing causality between health outcomes and traits; and health outcomes and preferences, as they are co-dependent.

Additionally, the relationship of traits and health outcomes are not assumed to be linear $(\frac{\partial \phi_{i,t}}{\partial P_{i,t}}) > 0$ for $P_{i,t} > \bar{P}$ for a threshold $\bar{P}$. Further can be seen in Borghans et al. (2008) and Almlund et al. (2011) which provide a complete view of how to incorporate personality traits into conventional economic models.

We now turn to the predicted power of personality traits and economic preferences on several outcomes.

2. Traits and preferences: determinants of various behaviors

Economic preferences and personality traits are significantly associated with various health, education, and labor market behaviors. These associations motivate their analyses. Thus, this section discusses the association between LOC, risk tolerance and time discounting with such behaviors.

2.1. Locus of control

Individuals facing a set of constraints with similar socio-economic characteristics are expected to take similar actions and therefore, have similar outcomes. This is, however, often not the case. One explanation is that individuals have different beliefs on the control they have over the consequences of their actions.

Recent developments in economics demonstrate that LOC has implications for job search effort, unemployment duration, and reservation wages. Caliendo et al. (2010); Cobb-Clark and Tan (2011); McGee (2015); McGee and McGee (2016) find evidence that individuals with internal LOC search more actively and have lower unemployment duration, whereas individuals with an external LOC have lower reservation wages. Indeed, individuals with internal LOC are also more likely to have higher wages than others (Cebi (2007), Semykina and Linz (2007); Heineck and Anger (2010); Salamanca et al. (2013)). This might be because those individuals are more likely to have higher educational attainment than individuals with external LOC (Feinstein (2000); Flouri (2006)). Additionally, individuals with internal LOC are more prone to eat well, to exercise regularly, to regularly visit doctors, and are less likely to drink excessive amounts of alcohol, than those with external expectations (Chiteji (2010); Cobb-Clark et al. (2014); Conell-Price and Jamison (2015)). As individuals with internal LOC have higher educational attainment, higher income, and better health, they save more (Cobb-Clark et al. (2016)) and invest more in riskier assets (Salamanca et al. (2013)).

2.2. Risk and time preferences

Risk and time preferences drive many individuals' decision-making. Given the importance of such preferences, a substantial empirical literature has produced strong evidence of the association between risk and time preferences with various labor market and health outcomes. We do not, however, list all existing studies.

Economic preferences are determinant of many labor market outcomes. Existing studies have examined how such preferences are related to job occupational choices (e.g. Van Praag and Cramer (2001); Cramer et al. (2002); Fuchs-Schundeln (2005); Ekelund et al. (2005); Bonin et al. (2007);Caliendo et al. (2010); Dohmen et al. (2011); Skriabikova et al. (2014); Koudstaal et al. (2015); Fossen and Glocker (2017)), reservation wages of unemployed job seekers (e.g. Feinberg (1977); Pannenberg (2010)), wage growth (e.g. Shaw (1996); Budria et al. (2013)), job mobility (e.g. Meier (2010)), and employment contract types (e.g. Guiso (2004)).

Economic preferences are also determinant of several health behaviors. The literature have related such preferences to smoking consumption (e.g. Barsky et al. (1997); Harrison et al. (2002); Khwaja et al. (2006); Khwaja et al. (2006); Chabris et al. (2008); Scharff and Viscusi (2011); Lawless et al. (2013); Brown and van der Pol (2014); Bradford et al. (2015)), drinking patterns (e.g. (Van Der Pol (2011); Bradford et al. (2015); Anderson and Mellor (2008); Andersen et al. (2014)), drug abuse (e.g. Blondel et al. (2007); Kirby (2004)), being overweight or obese (e.g. Komlos et al. (2004); Lusk and Coble (2005)), demand for medical screening tests (e.g. Picone (2004); Axon et al. (2009); Bradford et al. (2015)), choosing to get vaccinated (e.g. Chapman and Coups (1999); Nuscheler (2016)), with healthy eating habits (e.g. Galizzi and Miraldo (2017)), and with treatment and medical advice adherence (e.g. Brandt (2013); Van Der Pol et al. (2017)).

3. Traits and preferences: stable parameters?

"That which doesn't kill me makes me stronger" - Nietzsche's famous claim holds great resonance for many scholars in psychology, biology, and economics. They all have questioned whether traits and preferences are stable parameters.

3.1. Evidence from psychology

To apprehend stability, personality psychologists investigate whether some traumatic life events have changed the individuals personality. They refer to the term "post-traumatic growth" when such events induce positive psychological changes[23], and to "post-traumatic distress or disorder" when they induce negative psychological changes. As the latter is more linked with a medical approach, the rest of this sub-section will focus only on the former.

Tedeschi and Calhoun (2004) coined the term "post-traumatic growth", which captures the positive psychological changes they observed among their patients who were facing various challenging life events[24]. More precisely, they note:

"the individual has not only survived, but has experienced changes that are viewed as important, and go beyond what was the previous status quo. Post-traumatic growth is not simply a return to baseline it is an experience of improvement that for some persons is deeply profound" (p.4).

Such improvements can be the recognition of new possibilities, the development of more intimate social relationships, the increased perception of one's own strength, a greater engagement in spiritual questions, or an enhanced appreciation of life (e.g. Linley and Joseph (2004); Pals and McAdams (2004); Park and Ai (2006); Tedeschi and Calhoun (2004)).

Usually, personality psychologists rely on events defined by clinicians as "traumatic" as they threaten the integrity of the individual (Gray et al. (2004)). However, these events depend on the sample. For student samples, they often rely on a serious injury resulting from a motor vehicle accident (e.g. Calhoun et al. (2000)). For adult samples, they rely on experiences of natural disasters, serious accidents, physical assaults, or the diagnosis of life-threatening illnesses or chronic health conditions (e.g. Tennen et al. (1992); Helgeson et al. (2006)). To measure whether individuals facing such life events benefit from the experience, they use the Post-Traumatic Growth Inventory (PTGI), created by Tedeschi and Calhoun (1996). Such inventory asks participants to indicate on a 6-points scale the degree to which they had changed in the five domains outlined above[25].

[23] The reader can refer to Seligman studies (e.g.Seligman et al. (2002); Seligman et al. (2005); Seligman et al. (2006); Seligman (2008)). He is considered as the pioneer of positive psychology.

[24] For a review of evidence, controversies and future directions of post-traumatic growth as a positive personality change, the reader can refer to Jayawickreme and Blackie (2014).

[25] The scale ranges from 0 ("not at all"), to 5 ("a very great degree").

Results from longitudinal studies indicate that 58-79% of individuals facing such life events report positive changes in at least one domain (Affleck et al. (1987); Affleck and Tennen (1996); McMillen et al. (1997); Sears et al. (2003)). Further, long-term stability of post-traumatic growth remained stable over time (Bauer and Bonanno (2001)). Similarly, Hoerger et al. (2014) have investigated whether facing important life events change some traits of the Big-Five indicator. They found that individuals facing lung cancer would experience greater change in extraversion, agreeableness, and conscientiousness. Srivastava et al. (2003) have found similar results when individuals face severe health problems. The reasons for these changes are, however, less documented. It might be due to self-enhancement or active coping efforts (e.g. Tennen and Affleck (2009)).

3.2. Evidence from biology

In this sub-section, we provide evidence on changes in personality traits due to external forces that either damage parts of the brain or abruptly alter its chemistry.

Brain lesion studies provide evidence that personality can change. For example, Damasio et al. (2005) and Mataró et al. (2001) describe the behavior of Spanish patients who were impaled by an iron spike that injured both frontal lobes of the brain. After the accident, the patients had difficulty planning, became more irritable, and had problems regulating emotion, but did not display antisocial behaviors. Additionally, the effect of brain damage was persistent: after five years, patients who suffered traumatic head injuries (including being impaled) had social impairments, such as anger control (Lezak (1987)).

Neuroscientists have investigated the functioning of the brain in-depth. Some recent studies have examined how two parts of the brain, the amygdala and ventromedial prefrontal cortex, affect personality by regulating emotions. The amygdala aims to signal impulsive emotional responses to immediate environmental stimuli, such as reacting to a danger. In contrast, the ventromedial prefrontal cortex aims to signal reflective emotional responses to knowledge. These two parts of the brain conflict with each other when an individual makes decisions. Signals from the amygdala induce behavior that values immediate outcomes, whereas signals from the ventromedial prefrontal cortex reflect long-run considerations. The stronger signal dictates the resultant behavior. Individuals with damage on one of these parts of the brain exhibit changes in personality. For example, individuals with damage to the ventromedial prefrontal cortex tend to act impulsively and seem to overvalue short-term outcomes (e.g. Bechara (2005); Monterosso and Luo (2010))[26].

Some other studies show that it is possible to alter preferences and personality through experiments that change the brain's chemistry. For example, magnetic disruption of the left lateral prefrontal cortex can increase elicited discount rates (e.g. Figner et al. (2010)). Additionally, nasal sprays of oxytocin (hormone that plays a role in social bonding) increase trust in a game experiment (e.g. Kosfeld et al. (2005)). Drugs can also affect personality, such as paroxetine (a drug for treating depression), by decreasing neuroticism and increasing extraversion (e.g. Tang et al. (2009)).

3.3. Evidence from economics

In empirical economics, a key and unresolved issue is whether economic preferences and personality traits are stable; and whether and how they change over time due to personal events. Traditional economics theory has built on the assumption that such parameters are stable over time (Friedman (1953); Stigler and Becker (1977)). To-date, direct empirical evidence is mixed on this point.

The first set of literature has investigated the impact of various life events on the LOC using two, large representative panel surveys: the Household Income and Labor Dynamics in Australia survey (HILDA), and the German Socio-Economic Panel Study (G-SOEP)[27].

Using the HILDA, Cobb-Clark and Schurer (2013) find that medium-run (i.e. four years) changes in LOC are, on average, modest and concentrated among the youngest and oldest individuals[28]. They find that individuals who experience the birth of a child, a serious illness of a family member, or a worsening in their finances become more external, while those who change jobs, get promoted, or experience an improvement in their finances become more internal. Three other important life events: the death of a spouse, being retired, or being a crime victim have no significant impacts on LOC. Additionally, using a sample of Australian adolescents and young adults, Elkins et al. (2017) find that long term experience of pain is

[26]For other evidence of the link between personality traits and the different regions of the brain, the reader can refer to Canli (2006); DeYoung et al. (2010).

[27]Anger and Schnitzlein (2017) and Cobb-Clark and Schurer (2012) investigate the relationship between various life events and the Big-Five indicator.

[28]Evidence from early intervention in middle or high school has show that non-cognitive skills (e.g. self-esteem, perception of control) can be changed (Heckman and Kautz (2012)).

associated with an increase in external tendencies.

A second set of studies has analyzed the impact of life events on risk tolerance. Such is done by using the G-SOEP and the Health and Retirement Survey (HSR), which is a non-representative sample of the US population.

Sahm (2012) uses data on 18,625 hypothetical-gamble responses from 12,003 individuals between 45 and 70 years old from the HRS and finds only a very modest decline in risk tolerance over a 10-year window. She uses the diagnosis of a serious health condition (i.e. heart attack, stroke, cancer or lung disease) as life event measurements and concludes that risk preferences vary mainly across, but not within, individuals. Schurer (2015) investigates which socio-economic groups are most likely to change their risk attitude after facing an important health event (i.e. depression or high blood pressure). Using seven years of the G-SOEP and 36,105 individuals, she finds that the level of risk attitude remains stable between depressed and non-depressed individuals. She indicates, however, that individuals diagnosed with high blood pressures are more risk averse than others, when the former are aged 35-45. Like Schurer (2015), Decker and Schmitz (2016) also use the G-SOEP to assess whether a health shock (i.e. change in grip strength over time) influences risk attitude. Their approach enhances that of Schurer (2015) by using a regression adjusted matching approach, which allows for a more causal interpretation of the results. Using a sample of 6,642 individuals observed during nine waves, Decker and Schmitz (2016) find that a health shock significantly increases individual risk aversion. Further, Jones et al. (2018) investigate whether the effect of a health shock on financial risk attitudes differs by personality traits. Using 11 waves of the HRS, they find that extroverted individuals are more risk tolerant than others after facing health shocks (i.e. cancer, stroke, heart problems, lung problems, diabetes, high blood pressure, arthritis, and psychological problems).

In sum, it seems that both LOC and risk tolerance are not completely instable parameters; they might change after the occurrence of an important life event, and more precisely, after a health shock. We know very little, however, of the impact, magnitude and duration of such shocks on risk tolerance and LOC within European individuals. This PhD aims to bridge this gap.

4. Health shocks: definition and impact

4.1. Definition

A health shock refers to a health-related event occurring at the individual level. Analyzing such events is of first importance as individuals throughout their life are likely to face acute (e.g. traffic or workplace accidents) and/or chronic (e.g. diabetes, depression, epilepsy) health shocks. Indeed, in 2017 in the three countries analyzed in this thesis (i.e. Germany, the United Kingdom, and France), almost 20% of their population faced a health shock (measured by the number of hospital stays[29].). Therefore, understanding whether these health shocks trigger changes in traits and preferences is essential as it concerns a significant part of the German, French and United Kingdom population.

Economists have used various types of health events – summarized in Table 6 – to measure health shocks. They differ by whether the health event can be precisely identified or not. When the event is identified, the economics literature refers to major (12 studies) or minor (12 studies) health conditions. Major health conditions include cancer (lung or breast), heart attack, cardiovascular disease, myocardial infarction, and stroke. Minor health conditions include arthritis, diabetes, high blood pressure, depression, and anxiety. When the event is not identified, however, the literature distinguishes between four types of events: a drop in a self-reported health scale (nine studies), a hospital stay (five studies), the occurrence of a serious injury or illness (two studies), or a change in grip strength (one study). Overall, there are 15 different health shock measures.

[29] https://www.destatis.de/EN/FactsFigures/SocietyState/Health/Hospitals/Tables/GDHospitalsYears.html, https://www.kingsfund.org.uk/publications/nhs-hospital-bed-numbers, and https://www.atih.sante.fr/sites/default/files/public/content/2554/atih_chiffres_cles_2017.pdf

Table 6: Summary of the existing health shock measures

	Subgroups	Type of health shock	Number of studies
Identified	Major conditions	Cancers, heart problems, stroke.	12
	Minor conditions	Arthritis, diabetes, high blood pressure, psychiatric problems.	12
Not identified	Drop in a self-reported health scale		9
	Hospital stay		5
	Occurrence of a serious injury or illness		2
	Change in grip strength		1

Source: Cancers include lung and breast cancers; Heart problems include heart attack, cardiovascular disease, myocardial infarction; Psychiatric problems include depression, and anxiety disorders. The distinction between major versus minor conditions follows Cheng (2019).

4.2. Population impacted

We now turn to the population impacted by health shocks. Identified health shock measures are concentrated among older individuals (i.e. above age 50), except for diabetes and psychiatric problems that could affect anyone. Non-identified health shock measures affect all age categories. Additionally, both measures are used in developed countries: the United States, Australia, and European countries (i.e. Austria, Belgium, Denmark, France, Germany, Greece, Italy, Portugal, the Netherlands, Spain, Sweden, Switzerland, and the United Kingdom). Table 7 proposes a summary of the population (and their respective samples of analysis) impacted by health shocks.

Table 7: Cartography of who face health shocks

Subgroups	Countries	Samples
Major conditions	United-States	Individuals aged 51-61 years old (HRS) Individuals aged 51 and older (HRS) Males aged 20-64 years old (MEPS) Individuals aged 40-70 years old (PSID) Women aged 26-64 years old (HRS)
	Austria, Belgium, Denmark, France, Germany, Greece, Italy, the Netherlands, Spain, Swede and Switzerland	Individuals aged 50 and older (SHARE) or individuals aged 16 and older (GSOEP)
Minor conditions	United-States	Individuals aged 51-61 years old (HRS) Males aged 20-64 years old (MEPS)
	British	Individuals aged 15 and over (BHPS)
	Germany	Individuals aged 16 and over (GSOEP)
Drop in a self-reported health scale	Germany	Individuals aged 16 and over (GSOEP)
	Denmark, Netherlands, Belgium, France, Ireland, Italy, Greece, Portugal and Spain	Individuals aged over 16 (ECHP)
	British	Individuals aged 16 and older (BHPS)
	Spain	Individuals aged below 60 years old (ECHP)
Hospital stay	Sweden	Individuals aged between 30-59 years old (LOUISE + NPR)
	British	Individuals aged 15-40 years old (NCDS)
	Netherlands	Individuals aged 18-64 years old (GBA)
Occurrence of a serious injury or illness	Australia	Individuals aged 15 years old and over (HILDA)
	United-States	Individuals aged between 45-70 years old (HRS)
Changes in grip strength	Germany	Individuals aged 16 and over (GSOEP)

Note: GSOEP refers to the German Socioeconomic Panel; HRS refers to the Health and Retirement Study; SHARE refers to the Survey of Health Ageing and Retirement in Europe; BHPS refers to the British Household Panel Survey; HILDA refers to the Household, Income and Labour Dynamics in Australia; MEPS refers to the Medical Expenditure Panel Survey; ECHP refers to the European Community Household Panel; LOUISE refers to the population register covering demographic and socioeconomic information, and NPR is the National Patient Register; NCDS refers to the British National Child Development Study; GBA stands for the Municipality Register; PSID refers to the Panel Study of Income dynamics. There are all longitudinal datasets.

4.3. Outcome impacted

The consequences of health shocks reach far beyond health outcomes; they also impact labor and wealth. More precisely, 15 empirical studies have explored the relationship between health shocks and labor outcomes; ten empirical studies have explored the relationship between health shocks and health outcomes; and three empirical studies have explored the relationship between health shocks and wealth[30].

The literature on the relationship between health shocks and labor market outcomes focuses on two main aspects: the labor market participation and how such participation varies depending on individual socio-economic characteristics.

Concerning the labor market participation, studies show a negative and significant impact of health shocks, where individuals are more likely to be unemployed (Riphahn (1999); Garcia Gomez and Lopez Nicola (2006); McGeary (2009); Garcia-Gomez (2011); Garcia-Gomez et al. (2013); Conley and Thompson (2013); Bradley et al. (2013); Jones et al. (2015); Lundborg et al. (2015); Zimmer (2015); Jones et al. (2016); Trevisan and Zantomio (2016)), they are more likely to work less hours (Cai et al. (2014)), and more likely to retire earlier (Hagan (2009); Sanchez et al. (2019)).

The second set of literature shows that the effect of a shock depends on gender, initial level of income, and educational attainment. Regarding gender, Lindeboom et al. (2007) find that male employment rates at age 49 are about 23% points reduced due to health shocks, while for females it is 12% points. The nature of the shock matters; women are more likely to retire after facing cancer or lung disease, while it is after arthritis for men (McGeary

[30]For theoretical predictions of the effect of health shocks, the reader can refer to Table A3 in the Appendix Section.

(2009)). Further, wives are more likely to remain or start working when their husband faces a health shock, while husbands are more likely to withdraw from the labor force when their wives experience shock (Wu (2003); Garcia-Gomez et al. (2013)). Regarding income, Smith (1999) finds that households whose pre-illness income is above the median level face similar medical expenses but greater wealth losses than households with a below-median income level, when faced with a health shock. Garcia-Gomez et al. (2013) find opposite results: low-income individuals suffer worse from labor market consequences following a health shock than high-income individuals. Regarding educational attainment, Lundborg et al. (2015) find that the negative effect of health shocks is greater for low-educated than for high-educated individuals. More precisely, the authors find that employment rates for low-educated workers at age 40 are reduced by 21% after facing health shocks, while falling only 9% for high-educated workers at the same age.

The literature on the relationship between health shocks and health outcomes shows mixed evidence; such shock has both positive and negative effects on individual health.

Concerning the positive effects, Smith et al. (2001) find that smokers update their subjective probability assessments of living to age 75 more harshly than non-smokers and former smokers after a health shock. Further, Baji and Biro (2018) find that after a cancer diagnosis, stroke or heart attack, subjective longevity drifts back to pre-diagnosis levels. Therefore, they find an adaptation effect of subjective longevity, as health shocks seem to have only a transitory effect. Additionally, health shocks reduce smoking consumption among adult populations (Clark and Etile (2006); Falba (2005); Khwaja et al. (2006); Keenan (2009); Sundmacher (2012)). Such effects depend on the health shock measure: smokers do not respond to cardiovascular change (e.g. blood pressure) but do respond to larger cardiovascular problems and cancer diagnoses (Darden et al. (2018)). Additionally, Richards and Marti (2014) find that smokers with more financial risk exposure are more likely to invest in personal health after facing a health shock.

Concerning the negative effects of health shocks on health outcomes, Garcia Gomez and Lopez Nicola (2006); Lindeboom et al. (2007); Trevisan and Zantomio (2016) find that individuals facing such shocks have physical functioning and mental health deterioration. Such deterioration is greater for uninsured individuals (Doyle Jr (2005)).

The literature on the relationship between health shocks and wealth outcomes is scanter.

Smith et al. (2001) and Coile and Milligan (2009) find that health shocks are associated with a decrease in several financial portfolio assets (e.g. ownership in principal residences or vehicles), and that the effect of a shock strengthens with elapsed time. Lee and Kim (2008), however, find that the effect of such shocks on wealth tends to disappear over time for elders.

In sum, even though the types of shock differ greatly between studies, they do not differ much on their impacts. Health shocks have – broadly speaking – negative impacts on labor and wealth outcomes, but have mixed effects on health.

5. Intented contributions

This PhD dissertation aims to document whether personality traits and economic preferences are stable parameters after the occurrence of an important health event.

Given the impact of personality traits and economic preferences on life outcomes, it is a priority to know how much they can change. And if they change, to what extent do environment influences affect the developmental trajectories of such parameters?

To answer these questions, we will first study the impact of health events on perception of control (Chapter 1), and on risk tolerance (Chapter 2). Results of these two chapters will determine the next chapters. The finding that traits and preferences are stable parameters might call for a genetic transmission of such parameters (Chapter 3). To test for this assumption, we will investigate whether risk and time preferences were established *in-utero*. The level of testosterone received during pregnancy might explain, in part, differences in preferences among women and men. The finding, however, that traits and preferences are non-stable parameters may explain why individuals have healthier behaviors after facing health shocks (Chapter 4).

Generalizing that traits and preferences are non-stable parameters would be of interest for both academics and policy makers. For the former, most authors assume that traits and preferences are stable. This is convenient because it implies that such parameters can be controlled for when using fixed-effect or first-difference models. However, if traits and preferences are non-stable it implies that researchers relying solely upon these methods might not account for non-cognitive skills variation. For the latter, understanding what induces changes in economic preferences and personality traits may provide better insights into how individual choices change. This is key for policy design and their efficiency, especially in health where targeting and tailoring policies have shown limited impacts. Further, documenting such change might impact macroeconomic performance. Indeed, change in risk tolerance, for example, may lead to lower levels of self-employment or more conservative investment and voting behaviors, which have important implications for macroeconomic performance.

Additionally, documenting the drivers of individual choice changes is in line with recent implementations made in several OECD countries. For instance, in 2018, the French government created three departments within the "*Direction Interministérielle de la Transformation Publique*", with one specifically focused on "*Méthodes innovantes, sciences comportementales and écoute usagers*[31]" to enhance public policy efficiencies using recent findings in behavioral sciences.

We will know report all chapter contributions.

5.1. Chapter 1

Literature on the link between personality traits and shocks show mixed results, to date. The sensitivity of personality traits to shocks depends on their type and nature. However, whatever shock is under consideration, variation in personality traits are modest but significant.

We contribute to this literature in four ways. First, by providing the long run (i.e. ten year) impact of negative life events on LOC. Previous studies rely on the short (i.e. one or two years) or medium (i.e. five years) run impact of shocks. Second, by providing an estimate of the change in LOC, depending on the severity and chronicity of the shock. The number of hospital stays within a year measures severity, and the chronicity is measured using the number of overnight stays per hospital. Third, by providing some indications of the direction and magnitude of the LOC change for German individuals (whereas previous studies relied on Australian data). This is of importance as cultural dimensions may shape perceptions of control. Fourth, by providing additional support for the idea that either fixed-effect models or first-difference methods are not sufficient to control for personality traits.

To estimate the stability of LOC after a negative health shock (i.e. a hospital stay), we rely on the G-SOEP data. This dataset provides yearly longitudinal information on a rep-

[31] See more on https://www.modernisation.gouv.fr/nos-actions/les-sciences-comportementales.

resentative sample of the German population. Such data gives health, labor, psychological, and wealth outcomes of approximately 11,000 private households in the Federal Republic of Germany (from 1984 to 2016), and in Eastern German Lander (from 1990 to 2016). We exploit the richness of the panel by using a broad set of covariates in our analysis: age, educational attainment, income, gender, place of residence, employment and marital status, and self-reported health and insurance status. By doing so, we can control for many variables to remove confounding factors.

Using a fixed-effect model, we find that individuals facing a hospital stay have a decreased perception of control. More precisely, when using a LOC normalized index, individuals facing such health shocks decrease their LOC by 0.007 (p=0.001). This decrease is attributable to individuals that had, prior to the shock, lower values of LOC. Further, individuals facing several hospital stays or chronic disease have a greater decline in LOC than others. These findings are robust to several specification checks and show heterogeneous effects – older individuals are less likely to reduce their perception of control than younger ones. Therefore, LOC appears to be quite stable – but not set in stone – as some variation occurred.

5.2. Chapter 2

This chapter aims to analyze the stability of risk tolerance after the occurrence of a health shock (i.e. measured by heart problems, diabetes, depression, epilepsy, and cancer). It refers to existing literature that shows mixed results, to date.

Our analysis contributes to this literature by examining how such shock impact risk tolerance when the latter is measured by three different incentive-compatible experimental lottery games, and by three self-reported questions on willingness to take risks. Risk preferences are measured by two multi-pricelist binary lottery tasks (Holt and Laury (2002)), one with low and one with high monetary stakes; and one ordered lottery task (Binswanger (1980); Binswanger et al. (1981); Eckel and Grossman (2008a)). Risk attitudes are measured with three self-reported questions on the willingness to take risks in general, in health, or in finance (Dohmen et al. (2011)). Additionally, we can reconstruct the past health shock history of each respondent. Furthermore, by using a representative sample of the UK population, we can draw conclusions that are valid for the whole population.

This sample is a combination of the UK Household Longitudinal Study general questionnaire and the Innovative Panel included in the UKHLS. The former gives information on socio-economics characteristics of the respondent, whereas the latter provides risk tolerance estimates using a variety of methods.

Using propensity score matching on time-constant variables (i.e. educational attainment, gender, year of birth, working status of parents, and nationality of parents), we find no evidence that risk tolerance is affected by health shocks. The lack of association between shocks and risk tolerance is robust across all elicitation methods, both experimental and self-reported, and across several other robustness checks. The only notable exception is for the self-reported willingness to take risks in general, which is marginally and positively associated with past health shocks.

Although the formation of risk tolerance seems not to be determined by health events, biological factors may have played an important role in its determination. Such is investigated in Chapter 3.

5.3. Chapter 3

Our study focuses on an economic behavior that is often said to be sexually dimorphic: risk tolerance. Women are found to be, in general, more risk averse than men (see Byrnes et al. (1999); Croson and Gneezy (2009)). Although, social and cultural expectations for risk tolerance differ greatly between women and men, biological differences between sexes could also play an important role in behavior. Testosterone has been show to correlate with various behaviors: it enhances the motivation for competition and for dominance (Archer (2006)), reduces fear (van Honk et al. (2004); Hermans et al. (2006)), and is associated with gambling (Dabbs Jr and Morris (1990); Mazur and Booth (1998); Blanco et al. (2001)), and with risk tolerance (Sapienza et al. (2009); Apicella et al. (2008); Stenstrom et al. (2011)).

In this chapter, we investigate whether the digit ratio – a biomarker of prenatal testosterone exposure – is associated with several measures of current risk tolerance (both experimental and self-reported questions). Our study, therefore, participates in and contributes to the empirical debate on whether risk tolerance is partly determined before birth. Further, it also provides a better understanding of the origin of gender differences in risk tolerance.

We contribute to the existing literature in at least two ways. First, we consider a representative sample of the UK population rather than a sample of university students. Second, we relate both right- and left-hand digit ratios to various risk tolerance measures and time discounting. We rely on the same dataset from Chapter 2 (UKHLS) and used maximum likelihoods to estimate the expected value of the behavioral parameters for individual relative risk aversion and time discounting.

Results show that none of the measures of risk tolerance are significantly associated with right- or left-hand digit ratios. Risk tolerance is, therefore, unlikely to be determined before birth. We do find the same results for time discounting: both digit ratios are not significantly associated with time discounting.

5.4. Chapter 4

The final chapter aims to analyze whether acute health shocks (i.e. the first onset of an accident requiring medical care) influence health behaviors (i.e. smoking and alcohol consumption, and Body Mass Index).

Empirical evidence supports the existence of a significant and positive relationship between health shocks and health behaviors. Individuals facing such events are more likely to adopt healthy behaviors. However, if the health shock does not directly affect an individual (i.e. if the shock is experienced by a relative), health behaviors are not impacted.

We contribute to this existing literature in three ways. First, by analyzing the effect of a new type of health shock: traffic or labor market accidents leading to medical care. These types of events have not been investigated before because they are not considered direct consequences of health behaviors (such as with lung cancer or cardiovascular disease). Nevertheless, the shocks considered in these events are less subject to the reverse causality problem compared to those from lung cancer. Second, by using a French sample of electricity board workers, we are providing results on a never-studied population. Third, by increasing the number of health behaviors related to tobacco consumption (i.e. cigarettes, cigars, cigarillos, pipes), alcohol consumption and BMI. In effect, we are able to document potential reporting effects; individuals facing health shocks can reduce their tobacco consumption but simultaneously increase their alcohol consumption.

We are using a French panel (*Gazel*) dataset which covers 20,000 individuals (15,000 men and 5,000 women) working for the French national electricity board between 1989 and 2014. Using this yearly panel data highlights both inter-individual differences and intra-individual dynamics to help capture part of the complexity of decision-making in this domain.

By using a fixed-effect model, we find that there is a significant effect connecting shock to the number of cigarettes and tobacco units smoked, with an impact duration of five years after shock occurrence. Further, alcohol consumption is also reduced over three years, but BMI is not impacted. Individuals facing health shocks reduced smoking by an average of 1.2 cigarettes per week. However, this decrease is heterogeneous; heavy smokers are more likely to reduce their consumption than occasional smokers. Even though the decrease in the number of cigarettes is quite low, this result should be compared to stopping or reducing attempts. Such attempts last an average of 2.4 months (e.g. Segan et al. (2006); Herd et al. (2009)) that is 25 less than the decrease found in this study. Overall, our results show that health shocks seem to be a major determinant of tobacco consumption.

Chapter 1

Do Health Shocks Modify Personality Traits? Evidence from Locus of Control

Summary of the chapter:

This paper analyzes whether a personality trait, that is, locus of control, is stable after the occurrence of a health shock, namely a hospital stay. To do so, we use the German Socio-Economics Panel dataset. To identify the causal effect of such a shock on locus of control, we rely on a fixed-effects model. Results suggest that individuals facing health shocks are more likely to decrease their locus of control. That is, they tend to believe that their future outcomes are more determined by external factors than their own will. This decrease is attributable to individuals that had, prior to the shock, lower values of locus of control. Further, individuals facing severe hospital stays (i.e. measured by the number overnights) and those with chronic diseases (i.e. measured by the number of hospital stays within a year), have a higher LOC decline than others. This provides evidence that perception of control is not constant over time and could change after experiencing a traumatic health event.

Classification:

Keywords: health shocks; locus of control; hospital stays; panel data; fixed-effect model

JEL: C33; D91; I12

Acknowledgments:

I give special thank to Yves Arrighi, Andrew Clark, Brigitte Dormont, Daniel Herrera, Hélène Huber, Fabrice Le Lec, Nicolas Sirven, Lea Toulemon, Setti Rais, Lise Rochaix, Xavier Rousset, and Brendan Vannier for their discussions and suggestions.

I also thank all participants of the 2^{nd} LIRAES's doctoral day (Paris), of the 13^{th} doctorissime day, of the Work in Progress Seminar of Paris School of Economics (Paris), and of the 40^{th} Days of French Health Economists for all valuable feedbacks they have provided.

Contents of chapter 1

1. Introduction

Personality traits, often referred to as non-cognitive skills, comprise a large variety of traits such as self-efficacy, self-esteem, openness to experience, emotional intelligence or perception of control (see Almlund et al. (2011) for an overview)[32]. In this study, we focus on the latter, which is individuals' beliefs on the control they have on the occurrence of life events. Such perception is measured with the locus of control (LOC). LOC is a psychological concept capturing how future outcomes are perceived to be under one's control ((Rotter, 1954, 1966)). A distinction is typically made between internal and external LOC. Individuals with an internal LOC see future outcomes as being contingent upon their own behaviors. Those with an external LOC believe that future outcomes are, to a large extent, beyond their control (e.g. due to fate or luck).

Individuals' beliefs on what causes life events have major impacts on educational attainment, on labor market and health outcomes. Individuals with internal LOCs are more likely to have higher educational attainment (Feinstein (2000); Flouri (2006)), higher wages (Groves (2005); Cebi (2007); Semykina and Linz (2007); Heineck and Anger (2010)), and save more (Cobb-Clark et al. (2016)). These individuals are also more prone to eat well and exercise regularly (Cobb-Clark et al. (2014)), and are less likely to drink excessive amounts of alcohol (Chiteji (2010)[33]. Perception of control is, thus, predictive of various outcomes. Investigating whether LOC is stable has, therefore, important consequences on individuals' lives and more generally provides insights on the stability of non-cognitive skills.

The main objective of this paper is, therefore, to test the stability of LOC after a negative health shock (i.e. a hospital stay). This shock is likely to induce changes in the individual's perception of control. Individuals facing such a shock might reduce their perception of control (i.e. a LOC decrease) or increase their willingness to take control (i.e. a LOC increase). In

[32]Economists typically refer to these traits as non-cognitive skills to distinguish them from other productivity-related characteristics (e.g. ability, experience, or education), which are generally described as cognitive skills (Kuhn and Weinberger (2005); Cobb-Clark and Schurer (2013); Elkins et al. (2017)). Further, LOC captures beliefs that are distinct from – but complementary to – risk, time and social preferences (Becker et al. (2012)).

[33]Other papers relate the positive correlation between personality traits (measured by the Big-Five indicator), health and financial outcomes: Heckman et al. (2006); Roberts et al. (2007); Hampson et al. (2007) and Hampson et al. (2010). It seems that conscientiousness is the personality trait that best predict health outcomes. Brown and Taylor (2014) found that extraversion is significantly associated with higher household debt. For a global aspect of change in personality traits, one may refer to the Personality Psychology and Economic Handbook at section 8.

the former case, health shocks may reduce the individual's motivation to prevent future shocks while the reverse would hold true for a LOC increase. Determining the direction and the magnitude of such effects is thus an empirical issue.

The second objective of this study is to provide evidence on the endogeneity of personality traits. Empirical studies often assume that these personality traits are fixed[34]. However, there is an emerging literature on the instability of personality traits (measured with the Big-Five indicator[35] and the LOC). To investigate this question, four recent studies have analyzed the impact[36] of life events on the two above-mentioned personality traits, using two large representative panel surveys: the Household Income and Labor Dynamics in Australia survey (HILDA) and the German Socio-Economic Panel Study (G-SOEP).

Using HILDA, Cobb-Clark and Schurer (2013) find that medium-run (i.e. four years) changes in LOC are, on average, modest and concentrated among the youngest and oldest individuals. They find that individuals who experience the birth of a child, a serious illness of a family member, or a worsening in their finances become more external, while those who change jobs, get promoted, or experience an improvement in their finances become more internal. Three other important life events (i.e. death of a spouse, being retired, or being a crime victim) have no significant impacts on LOC. Using the same dataset and the same time span (i.e. four years), but using another personality trait, namtely the Big-Five, Cobb-Clark and Schurer (2012) find that health related events (i.e. serious illness or injury due to physical violence, or a new health condition), and labor market related events (i.e. worsening of finances, being retiring, being fired, or becoming unemployed) are significantly and negatively associated with conscientiousness and emotional stability. Family related events (i.e. death of a spouse, a child, a relative, or a friend, or being a victim of property crime), however, have no impact on personality traits. Further, using a sample of Australian adolescents and young adults, Elkins et al. (2017) find that long-term experience of pain is associated with an increase in external tendencies and with a decline in openness to

[34]In contrast, in the psychological literature, it is argued that personal experiences, especially recent ones, exert a greater influence on personal decisions than statistical summary information in books or via education (Nisbett and Ross (1980); Weber et al. (1993); Hertwig et al. (2004)).

[35]Such indicator summarizes five core personality traits: openness to experience, neuroticism, agreeableness, extraversion, and conscientiousness as a taxonomy for personality traits.

[36]Two other studies have investigated the reverse relationship, that is, the impact of personality traits on the probability to face a life event. Those studies find that individuals with internal LOC are less likely to face negative life events.

experience, conscientiousness and agreeableness. Using three waves (i.e. 2005; 2009; and 2013) of the G-SOEP, Anger and Schnitzlein (2017) find that involuntary job loss following a plan closure leads to an increase in openness to experience[37] for the average displaced worker and, to some extent, to a change in emotional stability, whereas the other dimensions of the Big-five personality traits remain unchanged.

To estimate the stability of LOC after the occurrence of a health shock, we also use the G-SOEP. We combine two sets of sub-samples. First, we extract information as to whether individuals had a hospital stay along with covariates (i.e. age, educational attainment, income, gender, place of residence, employment status, marital status, number of hospitalization, number of nights in hospital, nationality, self-reported health, and insurance status) for all available waves (from 1984 to 2015). Second, we extract LOC measures for the three available waves (2005, 2010, 2015)[38]. We combine these two sub-samples to obtain a three-years panel dataset with full information. Using such panel data highlights both inter-individuals' differences and intra-individuals' dynamics that are both important to capture possible variations in personality traits.

To take into account the non-randomness of the health shock, we rely on a fixed-effects model. Individuals that had one or more hospital stays in 2010 or in the following years constitute the treatment group. Those who never went to hospital over the period constitute the control group. Thus, in 2005 none of the groups are exposed, and in 2010 and after, only the treated group is exposed. We compare the difference in outcome (i.e. LOC level) after and before the shock for the treated and the control groups, controlling for the full range of individual covariates.

The results show that individuals facing a health shock decrease their perception of control. More precisely, when using a LOC normalized index[39], individuals facing a health shock decrease LOC by 0.007. This decrease is attributable to individuals that had, prior to the shock, lower values of LOC. Further, individuals facing severe hospital stays (measured with the number of overnights per hospital stay) or chronic illnesses (measured by the frequency

[37]The increase in openness following a job loss is driven by displaced workers who have a high level of education and who quickly find another job.

[38]Locus of control is also available in 1999 but since the scale is different (i.e. a 4 items-scale rather than a 7 items-scale), it is not used in the present study.

[39]This means that the minimum value of LOC is mapped to 0, and the maximum value of LOC is mapped to 1. Thus, the entire ranges of value of LOC from minimum to maximum are mapped to the range 0 to 1. The histogram of this measure is shown in Figure 1 in the appendix.

of hospital stays per year) have a greater decline in LOC than others. These findings are robust to several specification checks: to a balanced panel dataset; to maternity hospital stays (a particular type of hospital stays); to past non-health shocks (i.e. death of partner, death of mother, death of father, and being divorced), and show heterogeneous effect: older individuals are more likely to reduce their perception of control than younger ones. Our results corroborate the above-mentioned findings in the literature (Cobb-Clark and Schurer (2012); Boyce et al. (2013); Cobb-Clark and Schurer (2013); Anger and Schnitzlein (2017); Elkins et al. (2017)) on the instability of personality traits.

Our paper improves upon the existing literature in at least five ways. First, it provides the long-run (i.e. 10 years) impact of negative life events on personality traits. Second, it provides an estimatye of the change in LOC depending on the severity and the chronicity nature of the shock. To do so, we document whether longer (respectively, shorter) hospital stays lead to greater (respectively, smaller) LOC changes and whether repeated (respectively, unique) hospital stays impact such change. Third, it provides some indications of the direction and magnitude of the LOC change for German individuals (whereas previous studies mostly relied on Australian data). This is of importance as cultural dimensions may determine perception of control. Fourth, it provides additional support for the idea that fixed effect models or first-difference methods are not sufficient to control for personality traits. Fifth, this study contributes to the empirical debate on whether shocks can be considered as a new and credible source of information that individuals use to update their personal beliefs.

The first section describes the dataset. Section 2 presents the empirical strategy. Results and robustness checks are presented respectively in sections 3 and 4. Section 5 discusses the findings and reports limitations. The last section concludes.

2. Data

The G-SOEP is a longitudinal dataset of approximately 11,000 private households in the Federal Republic of Germany survey from 1984 to 2016, and Eastern German länder from 1990 to 2016[40]. All household members aged 16 or older are eligible for inclusion in the regular panel survey. Variables include household composition, employment, occupation,

[40]See more on Wagner et al. (2007). This dataset is funding with public sources Krupp (2008).

earnings, health, and personality traits measures. G-SOEP's rich dataset enables us to control for a large number of covariates to remove confounding factors.

2.1. Variables of interest

To measure the shock, we rely on the following question that is present over the whole span of the panel: "did you have to stay in hospital for one or more nights during the previous year?" We define a dummy variable set to one if individuals face such a shock, and zero otherwise. We collect information on hospital stays for all individuals. We therefore reconstruct each individual's health shock history since 1984. Further, as LOC is only recorded in three waves (2005, 2010, and 2015), we aggregate hospital stays information to coincide within these three waves. More precisely, in 2005 we aggregate for each person, hospital stays information, from 1984 to 2005; in 2010 we aggregate hospital stays information from 2006 to 2010, and in 2015 we aggregate hospital stays information from 2011 to 2015. We have, thus, for all individuals a three time period analysis. To implement a fixed-effects model, we consider individuals that have had health shocks after 2005. We select out those who had health shocks before 2005[41].

LOC is measured using the Rotter scale. It contains 10 questions on individuals' perception of control over their life outcomes. The different components of the LOC scale are summarized in Table 1. Individuals have to indicate whether or not they agree with10 statements on a 7 points-scale[42]. We aim to group these questions into 2 groups, where the first would aggregate information on internal questions, and the second on external ones. To do so, we adopt the same approach as Caliendo et al. (2010) and Cobb-Clark and Schurer (2013) and run a multi-component analysis. Our results corroborate theirs and indicate that questions 1, 6 and 9 load onto an internal factor, and 2, 3, 5, 7, 8, and 10 loads onto an external factor[43]. Item 4 does not load onto either factor and is therefore dropped from the analysis. We then construct an internal index (the average of the internal questions); an external index (the average of the external questions); and a full index (the average of both

[41]Individuals in the treatment, therefore have a health shock only after 2005, and not before. Individuals in the control group never had any health shock (but we are not able to provide with certainty that they had no health shock before entering in the dataset).

[42]The scale ranks from 1 (I do not agree at all) to 7 (I agree fully).

[43]This analysis could be seen in Figure 2 in annex.

internal and external questions with the external questions reversed)[44]. To better interpret variations in LOC, we use a normalized LOC index[45]. It simplifies the interpretation of the full index as it ranges from 0 to 1. For this indicator, the higher (lower, respectively) the value, the more internal (external, respectively) is the individual.

Table 1: Components of locus of control

	2005				2010				2015			
	N	Mean	SD	Median	N	Mean	SD	Median	N	Mean	SD	Median
Components of locus of control (1: I do not agree at all, 7: I agree fully)												
Q1. My lifes course depends on me	17,466	5.459	(1.363)	[6.000]	14,064	5.431	(1.291)	[6.000]	19,888	5.599	(1.266)	[6.000]
Q2. Haven't achieved what I deserve	17,466	3.272	(1.802)	[3.000]	14,064	3.259	(1.768)	[3.000]	19,888	3.196	(1.753)	[3.000]
Q3. What you achieve depends on luck	17,466	3.632	(1.698)	[4.000]	14,064	3.504	(1.638)	[3.000]	19,888	3.629	(1.670)	[4.000]
Q4. Influence on social conditions through involvement	17,466	3.510	(1.659)	[4.000]	14,064	3.773	(1.580)	[4.000]	19,888	3.891	(1.632)	[4.000]
Q5. Others make crucial decisions in my life	17,466	3.118	(1.720)	[3.000]	14,064	3.099	(1.670)	[3.000]	19,888	3.023	(1.679)	[3.000]
Q6. Success takes hard work	17,466	6.065	(1.084)	[6.000]	14,064	5.948	(1.113)	[6.000]	19,888	5.910	(1.141)	[6.000]
Q7. Doubt my abilities when problems arise	17,466	3.334	(1.684)	[3.000]	14,064	3.159	(1.624)	[3.000]	19,888	3.250	(1.647)	[3.000]
Q8. Possibility are defined by social conditions	17,466	4.534	(1.514)	[5.000]	14,064	4.492	(1.450)	[5.000]	19,888	4.453	(1.478)	[5.000]
Q9. Abilities are more important than effort	17,466	4.956	(1.333)	[5.000]	14,064	4.794	(1.333)	[5.000]	19,888	4.898	(1.334)	[5.000]
Q10. Little control over my life	17,466	2.721	(1.551)	[2.000]	14,064	2.674	(1.477)	[2.000]	19,888	2.697	(1.487)	[2.000]
Aggregated LOC indices												
Internal index ([Q1 + Q6 + Q9]/3)	17,466	5.494	(0.861)	[5.667]	14,064	5.391	(0.837)	[5.333]	19,888	5.469	(0.847)	[5.333]
External index ([Q2 + Q3 + Q5 + Q7 + Q8 + Q10]/6)	17,466	3.435	(1.037)	[3.333]	14,064	3.364	(1.015)	[3.333]	19,888	3.375	(1.002)	[3.333]
Full index ([Q1 + Q6 + Q9 + R(Q2 + Q3 + Q5 + Q7 + Q8 + Q10)]/9)	17,466	4.874	(0.774)	[4.889]	14,064	4.887	(0.754)	[4.889]	19,888	4.906	(0.734)	[4.889]

Note: this table shows the components of locus of control for waves 2005, 2010, and 2015. Source: G-SOEP data.

Furthermore, we also exploit the richness of the panel by using a broad set of covariates in our analysis. In particular, age, educational attainment[46], income (in log)[47], gender[48], place of residence[49], marital status[50], number of hospital stays[51], number of nights in hospital[52], self-reported health[53], and insurance status[54].

[44]This allows interpreting the full indicator as follow: the higher (lower, respectively) its value, the more internal (external, respectively) an individual is.

[45]It sets to 0 the lower value taken by the LOC full index and to 1 its higher value. This makes the LOC variation easier to interpret. The lower (higher, respectively) the value of the normalized index, the more external (internal, respectively) is the individual.

[46]Individuals' level of education is a dummy variable equal to one if he or she reports having a secondary or a upper secondary school degree, 0 otherwise.

[47]Income is the log of the yearly individual income.

[48]Gender is a dummy with value one for women and zero for men.

[49]Place of residence is equal to 1 if individuals live in Eastern regions, and 0 if they live in Western regions.

[50]Individuals' marital status is equal to 1 if they are in couple, and 0 otherwise.

[51]Number of hospital stays within a year is a dummy variable (equals to one when above the average).

[52]Number of nights in hospital within a year is a dummy variable (equals to one when above the average).

[53]Self-reported health is a categorical variable coded from 0 to 10 (0 for being in poor health, 10 in excellent health).

[54]Insurance status is equal to 1 if individuals have a private health insurance and 0 if they had a compulsory health insurance.

2.2. Descriptive statistics

We observe 41,685 observations in our unbalanced panel dataset. In this sample, 22,45% of the individuals face a health shock. Individuals in the treatment group (i.e. those who face health shock) have particular characteristics that are not shared by those in the control group (i.e. those who never faced a health shock). For instance, the treated group is significantly older (46,7 years old, on average, compared to 40,3 for the control group), are more likely to have a lower income, to live in Eastern region, to have no private insurance plan, to be more educated and to be a woman, than individuals in the control group. Individuals have, on average, 2.3 hospital-stays and stay 22 nights in hospital. Individuals facing a health shock are also more likely to have lower LOC than those in the control group. This provides first evidence that LOC may change after facing such event. This calls for a quasi-experimental empirical strategy to take into account the non-randomness of the shock. Importantly, looking at the within variation of treated individuals reveals that before the shock, they reported higher health than after. Furthermore, they also reduce their perception of control, as LOC is lower after than before the occurrence of the shock. This suggests that treated individuals have more external LOCs after the occurrence of health shocks. Additional descriptive statistics between groups can be found in Table 2.

Table 2: Characteristics of sample by groups

	Treated and control groups			Treated group		
	Treatment group	Control group	Difference	After	Before	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Locus of Control	0.631	0.637	-0.006***	0.629	0.636	-0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Age	46.687	40.370	6.316***	47.800	46.267	1.533***
	(0.137)	(0.098)	(0.165)	(0.162)	(0.259)	(0.308)
Being in couple	0.124	0.122	0.002	0.134	0.097	0.036***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Income (log)	9.789	9.843	-0.054***	9.725	9.947	-0.222***
	(0.008)	(0.010)	(0.013)	(0.018)	(0.013)	(0.023)
Living in Eastern region	0.242	0.202	0.039***	0.234	0.262	0.029***
	(0.002)	(0.003)	(0.004)	(0.006)	(0.004)	(0.007)
Private insurance plan	0.137	0.143	0.006*	0.126	0.168	0.042***
	(0.002)	(0.003)	(0.003)	(0.005)	(0.003)	(0.006)
Self-reported health	4.623	4.631	0.007	3.486	5.056	1.570***
	(0.015)	(0.016)	(0.024)	(0.015)	(0.020)	(0.035)
Educated	0.527	0.484	0.044***			
	(0.003)	(0.004)	(0.005)			
Female	0.557	0.463	0.095***			
	(0.003)	(0.004)	(0.005)			
Nb. of hospital stays	2.295					
	(2.917)					
Nb. of overnights	22.474					
	(36.852)					
Observation	15,586	26,099		4,266	11,320	

Note: this table shows the difference in mean of all covariates between the treated and the control group (column 3) and within the treatment group (column 6). Individuals in the treatment group have characteristics not shared with those of the control group (e.g. lower LOC and are older). After the shock, treated individuals are in worse health and have lower LOC.

3. Empirical strategy

3.1. Empirical model

To estimate the causal effect of hospital stays on LOC, we use the following econometric fixed-effects model, which removes unobservable individual specific effects that are constant over time (e.g. genetic factors).

$$LOC_{i,t} = \beta.(HealthShock_{it}) + \phi.\mathbf{X_{i,t}}' + \gamma_i + \epsilon_{i,t} \tag{1}$$

In equation (1), $LOC_{i,t}$ refers to the normalized LOC index of an individual i at time t. $HealthShock_{i,t}$ is a dummy variable equals to 1 for years after the shock for individuals in the treatment group, 0 otherwise. $\mathbf{X_{i,t}}'$ is the covariate matrix (only the time varying variables described in the previous Section), γ_i are individual fixed-effects, and $\epsilon_{i,t}$ is an error term that is assumed to be orthogonal to all characteristics.

While facing a health shock may have an average impact on LOC, significant disparities may exist in the population and need to be further documented. To study these heterogeneous effects, we provide information on particular subgroups. We specifically analyze the impact of health shocks on LOC by the severity of shocks (measured with the number of overnights in hospital), and by the frequency of hospital stays within a year. Further, we provide heterogeneous effects depending on the initial level of LOC. To do so, we create an indicator based on the LOC indicator, which takes the value of 1 if an individual has a higher than median LOC, and 0 otherwise. We also perform a quartile regression to assess where in the LOC distribution the change is most significant.

3.2. Identification

Our identification approach exploits the probability that an individual may face one or more hospital stays. The focus on this specific type of health event is motivated by their severity because they are in most cases unanticipated. Even in the case individuals might envisage experiencing a similar health shock (e.g. due to unfavorable genetic factors or due to family past health history), uncertainty remains, if not on occurrence, on the time of potential occurrence. Previous works on the relationship between health and labor market behaviors have adopted similar measures (e.g. Lindeboom et al. (2007); Garcia-Gomez et al. (2013)).

For β to measure the causal impact of health shocks on individuals' LOC, there should be no endogeneity issues. We are not able, however, to ensure that this is not the case. Health shocks and LOC may be either correlated with unobservable variables, or subject to reverse causality, or both. Regarding reverse causality, individuals with an internal LOC are more likely to be resilient after health shocks than those with external LOC (Schurer (2014); Buddelmeyer and Powdthavee (2016))[55]. Regarding unobservable variables, risk tolerance and personality traits (e.g. optimism)[56] could be good candidates: they may influence both LOC and the probability to face a shock. Their omission, therefore, may bias our results. This concern may be alleviated if risk tolerance or optimism are constant over time as the fixed-effects model purges time invariant unobservable variables.

Further, such model, does not take into account time variant unobserved variables that influence both the probability face a shock and the LOC (e.g. choice of transportation: commuting or personal vehicle; type of job preferences).

4. Results

In this section, we first present OLS estimates of equation (1) using pooled and fixed-effect analyses. We then provide results for sub-group analyses. We conclude by performing robustness checks.

4.1. Main results

Table 3 shows the effect of the health shock on the LOC's normalized index using the approach described in Section 2. We report results as follow. Columns 1 and 2 give the findings of the pooled analysis (without and with control variables). Columns 3, 4 and 5

[55] An instrumental variable method, using health care services at the individual level, would be a promising strategy to purge such endogeneity. However, do date, finding such a variable is challenging because the catchment area in Germany is not well defined or documented (Bauer and Groneberg (2016); Greiner et al. (2018)).

[56] Religion has been shown to insure against some adverse life events (e.g. unemployment). Further, Catholic and Protestants suffer less from unemployment than do the non-religious (Clark and Lelkes (2005)). The reader can also refer to Smith et al. (2003)' meta-analysis on religiousness and its influence on stressful life events.

indicate the results of the fixed-effect model. Column 3 provides results without control variables and individual fixed-effects. Column 4 adds control variables. Column 5 adds individual fixed-effects. When using a pooled analysis, results are not significant. Indeed, significant disparities within individuals need to be taken into account, which is done using the fixed-effect analysis. By doing so, compared to those who do not face a health shock, treated individuals reduce their LOC by 0,007.

Table 3: Pooled and fixed-effects analysis

	Pooled analysis		Fixed-effects analysis		
	LOC	LOC	LOC	LOC	LOC
	(1)	(2)	(3)	(4)	(5)
Health Shock	-0.007***	0.001	-0.010***	-0.008***	-0.007***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Individual covariates	No	Yes	No	Yes	Yes
Individual Fixed-effects	No	No	No	No	Yes
Observations	41685	41685	41685	41685	41685
R^2	0.001	0.031			0.002

Note: this table provides the effect of health shock on locus of control using a pooled analysis (columns 1 and 2) and a fixed effects model (column 3, 4, and 5). Facing such a shock reduce LOC of control by 0.007. Individuals, therefore, become more internal after the shock.

The impact of a health shock might be different depending on how long an individual stays in hospital, and if he or she has many hospital stays in a given year. To document this potential source of heterogeneity, Table 4 exhibits sub-group analysis results, with columns 1 to 5 providing the effect of the shock depending on the number of hospital stays per year: 1 hospital stay (column 1); 0-2 (column 2); 0-3 (column 3); 0-4 (column 4); and 5 and more (column 5). Results indicate that individuals facing 2 to 4 hospital stays are more likely to reduce their perception of control than others. Those with one and more than 5 hospital stays do not significantly change their perception of control. This result might suggest that frequency matters up to a certain threshold, beyond which there are no more changes in LOC. Columns 6 to 9 provide an assessment of the role played by severity, as measured by the number of overnights. Results show that only those who stay more than 15 days (column

9) reduce their LOC. Results indicate that the higher the severity, the more important the LOC decrease. Overall, our findings point to the fact that LOC change is dependent of both the severity and the frequency of the shock.

Table 4: Sub-group analysis:
Comparing subgroups with different lens of overnights

	Nb. Hospital stays					Nb. overnights			
	LOC	LOC	LOC	LOC	LOC	LOC	LOC	LOC	LOC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	(0-1)	(0-2)	(0-3)	(0-4)	(5 and more)	(0-2)	(0-7)	(0-14)	(15 and more)
Health shock	-0.005	-0.005*	-0.006**	-0.006**	-0.011	0.007	-0.005	-0.004	-0.015***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.006)	(0.003)	(0.003)	(0.005)
Individual covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31311	34933	36685	37631	25487	26138	31372	34592	4428
R^2	0.002	0.002	0.002	0.002	0.002	0.001	0.002	0.002	0.007

Note: individuals facing intermediate number of hospital stays are more likely to reduce their perception of control. Those facing 15 or more overnights are also more likely to reduce thier LOC.

Table 5 provides more detailed information on those who reduced their LOC[57]. To do so, such Table provides a quintile regression at 0.10; 0.25; 0.50; 0.75; and 0.90. It documents the impact of health shocks on the LOC distribution. Results show that the first and second quintiles (in column 2 and 3, respectively) are not statistically significant. At quintile 0.5, 0.75 and 0.9 (in column 4, 5, and 6, respectively) results are statistically significant. The magnitude of the coefficients increases, as the quintiles analysis gets closer to 0.9. Facing a health shock reduces the perception of control for those who previously believed that had more control over their life outcomes. Individuals who already had a low perception of control seem not to change their perception. While facing a health shock have an average negative impact on LOC (column 1 – baseline), significant disparities exist in the sample. Individuals with higher perception of control, prior to the shock, reduce more their perception that other. Individual with higher LOC therefore, drives the negative average impact.

[57]Other heterogeneous effects, among which gender or educational attainment, are available on request. In our results on LOC change following a health shock, we do not find a statistical relationship with being a female and or being more educated (reaching at least an upper degree).

Table 5: Quantile analysis

	Baseline	Quantile regression				
		Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
	(1)	(2)	(3)	(4)	(5)	(6)
Health Shocks	-0.007***	-0.005	-0.006	-0.007***	-0.008***	-0.008***
	(0.002)	(0.005)	(0.004)	(0.002)	(0.002)	(0.003)
Individual covariates	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41685	39020	39020	39020	39020	39020
R^2	0.002					

Note: individuals with high LOC before the shock are those who reduced more their perception of control than others.

4.2. Robustness checks

To test the sensitivity of our results, we provide four robustness checks in Table 6. First, to assess the attrition problem that occurs when working on panel data, we provide the baseline equation using a balanced panel (column 2). Second, results in column 3 control for past non-health shocks (column 3) that individuals may have faced, such as death of partner, of a parent, or of a friends, as well as divorce. Controlling for such non-health shocks matters as individuals' ability to cope with current health shocks is influenced by past events (e.g. Powdthavee (2014)). Third, we control for childbirth (column 4) as this type of hospital stay cannot be considered as a health shock, but may have an impact on LOC. Fourth, we document the effect of LOC change on individuals aged 60 or more (column 5). Results show that older individuals facing a health shock are more likely to reduce their perception of control than younger ones. This is in line with other studies on the stability of personality traits over the life cycle: change in such traits is modest and concentrated among the younger and the older individuals (Cobb-Clark and Schurer (2013); Elkins et al. (2017)).

Table 6: Robustness checks

	LOC	LOC	LOC	LOC	LOC
	(1)	(2)	(3)	(4)	(5)
	(Baseline)	(Balanced panel)	(Past-non health shocks)	(Child birth)	(Older cohort)
Health Shock	-0.007***	-0.009***	-0.007***	-0.007***	-0.003
	(0.002)	(0.003)	(0.002)	(0.002)	(0.254)
Older cohort					0.013***
					(0.002)
Health Shock × Older cohort					-0.010
					(0.391)
Individual covariates	Yes	Yes	Yes	Yes	Yes
Individual Fixed-effects	Yes	Yes	Yes	Yes	Yes
Past non-health shocks	No	No	Yes	No	No
Child birth	No	No	No	Yes	No
Observations	41685	10764	41685	41685	18304
R^2	0.002	0.003	0.002	0.002	0.002

Note: this table provides the robustness checks of the effect of health shock on locus of control. All these specifications confirme the sign, the magnitude and significant level effect of such shock.

5. Discussion and limitations

Results show a significant and negative relationship between health shocks and perception of control. These results are, however, small in magnitude. Further, it seems that individuals facing severe and chronic shocks, as well as individual with more external LOC, are more likely to reduce their perception of control.

Several mechanisms can be offered for our results. Individuals with an internal LOC tend to invest earlier and more intensively in education, health and social capital than individuals with an external LOC (e.g. Coleman and DeLeire (2003); Cobb-Clark et al. (2014)). This investment may act as an indirect psychological insurance to prevent future shocks. Moreover, individuals with internal LOC may have accumulated more hedonic capital (i.e. have a larger stock of psychological resources) and are therefore more resilient (Graham and Oswald (2010))[58]. It is possible that the non-significance of LOC change among internal individuals is caused by this long-run accumulation of human and hedonic capitals in earlier

[58]More precisely, Graham and Oswald (2010) define hedonic capital as “social relationships whit partners, friends, and colleagues; health; self-esteem; status; and meaningful work [. . .]. These are stock in that they rely on past inputs and are carried across time period.”

ages. Individuals with an external LOC may also be more likely to have a self-serving bias (e.g. Heider (2013); Campbell and Sedikides (1999)). That is, they are less prone to take credit for personal success and blame external factors for personal failure. These individuals may refuse to accept that the shock can be preventable and blame it to fate. This self-serving bias may explain why our results are stronger for individuals with an external LOC.

Further, individuals with internal LOC may also have better coping strategy to counterbalance episode of ill health[59]. Conscientiousness may also play a role in the coping strategy because conscientious individuals are more effective at following protocols and treatment advice from their physicians (e.g. Christensen and Johnson (2002)). Many studies found that conscientiousness is also associated with control beliefs (e.g. Marshall and Ferenczi (2015)) and with active problem-focused coping behavior (e.g. Watson and Hubbard (1996)).

Results face limitations due the fact these findings are derived for German individuals, so that it may not be generalizable for other countries. Indeed, cultural dimensions may determine control perception, influencing individual answers to LOC questions. Values and norms are forces that can induce behavioral changes. Since culture reinforces certain personal characteristics at the expense of others, one could expect that some cultures be more aligned with internal orientation than others (Parsons and Schneider (1974); Reltz (1974); Mueller (2001); Spector and Miller (2002)). Research comparing countries has shown in more individualistic cultures, individuals have higher internal LOC (Mueller (2001))[60]. As Germany is more likely to be an individualistic country, respondents may over-estimate their internal control. Plus, we do not observe religious status of individuals. Such a variable can influence the way one recovers from the shock and his or her perception of control.

Hospital stays are chosen for the following advantages. First, they are a public health issue as 23% of the German population has had a hospital stay in 2017[61]. Second, by using

[59]Evidence of individual coping responses to negative life events is well established in the psychological literature defined as post-traumatic growth by Tedeschi and Calhoun (2004)). For more evidence, see Galatzer-Levy and Bonanno (2013); Lotterman et al. (2014); Orcutt et al. (2014); Jayawickreme and Blackie (2014)

[60]Individualistic society refers to places where social ties and commitments are loose. Collectivism society refers to places in which people are integrated in strong, cohesive groups throughout a lifetime (Hofstede (1991)).

[61]See more general statistic of German hospital: `https://www-genesis.destatis.de/genesis/online/data;sid=F340768FDD9A338CCCF4762380D04276.GO_1_4?operation=abruftabelleBearbeiten&levelindex=2&levelid=1558537391287&auswahloperation=abruftabelleAuspraegungAuswaehlen&auswahlverzeichnis=ordnungsstruktur&auswahlziel=werteabruf&selectionname=23111-0001&auswahltext=&werteabruf=Value+retrieval`.

hospital stays it was possible to document the heterogeneous effect on LOC depending on the severity and the chronicity of the shock. Third, individuals have no influence neither on the duration of the stays nor on the decision to get hospitalized. This is especially the case in Germany since the introduction of diagnosis-related groups type payment system in 2000, which classifies patients into groups according to the consumption of resources required to treat their condition (e.g. Schurer (2014)). Fourth, even if a hospital stay is not completely exogenous, an individual can't really choose the moment at which he or she will enter the hospital[62].

Hospital stays have, however, disadvantages. First, it is unlikely that all hospital stays refer to exogenous and random shocks. For example, accidents in Germany account for a very small part of total hospital stays. In 2017, 1.5% of all hospital stays were due to accidents involving partial or slightly injured persons, and 2% were due to accidents involving seriously injured persons. Adding these figures lead to 3.5% the number of hospital stays due to accidents. It is therefore far away from the 23% we have in our sample. The most frequent reasons for hospital stays was linked with parasitic diseases, intestinal infectious diseases and bacterial diseases . Second, we do not have information of the individual perception of the severity of the shock. This might be at least as important as medical severity. Third, we do not have information on whether the hospital stay was linked with a psychiatric stays, which may have an importance when looking at perception of control.

6. Conclusion

This paper offers new evidence on how German individuals have changed their locus of control after experiencing a hospital stay. Although the empirical results do not necessarily establish a strict causality (due to a number of potential unobservable determinants), the findings nevertheless suggest that there are significant effects running from the shock to the perception of control. Individuals facing a hospital stay decrease their perception of control by comparison with those who do not face such a shock.

A direction to pursue could be to examine variance in personality traits (e.g. optimistic

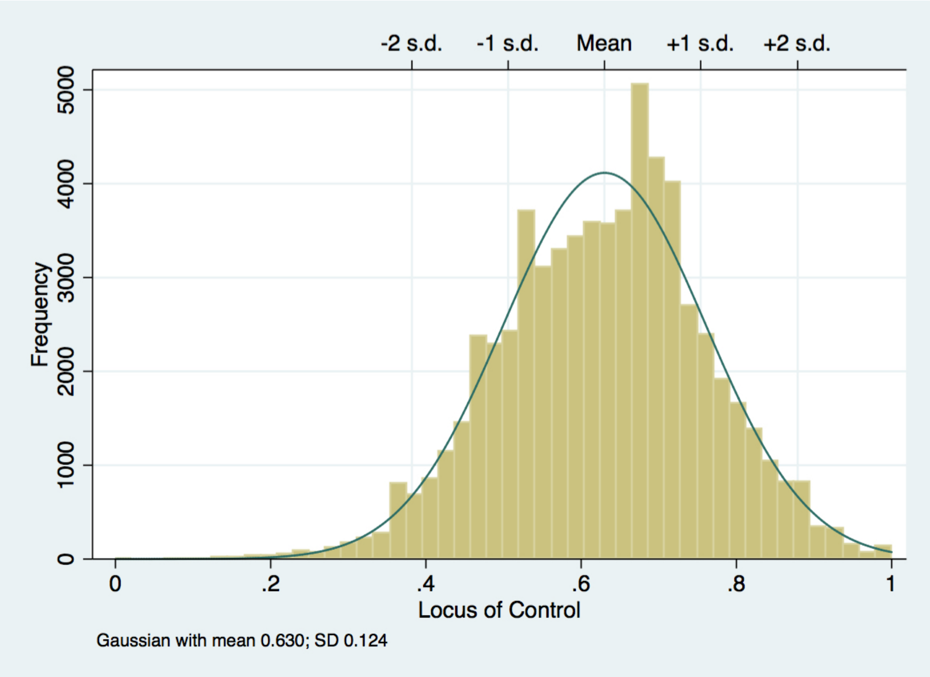
[62]One way to reassure the reader about such exogeneity would be to have information on the precise day of the week an individual enters the hospital as he or she have clearly no influence on when the hospital has a free room. Due to data limitation, I am not able, however, to provide this information.

individuals, high self-esteem person) among individuals facing health shocks to analyze if they develop better coping strategies. Further, individuals with an external LOC may not enter the health system, as they believe their health in beyond their control. It may be worth designing individualized care pathways that take into account patients' behavioral characteristics.

Other studies will need to be carried out in different settings and countries, in order to give more support to our findings. And an open question remains, as to which personality traits public policy should target.

7. Appendix

Figure 1: Distribution of the Locus of Control index



Note: The distribution of the LOC index ranks from 0 to 1, with an average of 0.63 and a standard deviation of 0.124.

Figure 2: Principal factor analysis

Note: factor 1 and factor 2 represent respectively external and internal locus of control. External locus of control aggregates questions in the following way: ([Q2 + Q3 + Q5 + Q7 + Q8 + Q10]/6), and internal locus of control aggregates questions in the following way: ([Q1 + Q6 + Q9]/3). Question 4 seems not to be neither external nor internal.

Chapter 2

Association between Health Shocks and Risk Tolerance: (No) Evidence from a UK Representative Sample

This chapter was co-authored
with **Matteo M. Galizzi** and **Sara Machado**.

Summary of the chapter:

We investigate whether past health shocks influence risk tolerance in a representative sample of the UK population. Using the Innovative Panel of the UK Household Longitudinal Study, we reconstruct each individual's health shock history. Risk tolerance is measured using both incentive-compatible experimental tests for risk preferences and self-reported Likert-scale questions for risk attitudes. The former allow us to estimate the individual risk aversion under standard expected utility theory and constant relative risk aversion assumptions, The maximum likelihood estimations account for the complex survey design by using sampling weights to draw valid inference for the adult population in the UK, and adjust standard errors at cluster and primary sampling unit levels. We estimate the propensity score of suffering a health shock using time-invariant or pre-determined demographic and socioeconomic variables which are unaffected by the health shocks. The respondents in the "treatment" group, that is, those who have suffered a health shock, are then matched, based on this propensity score, with the individuals who have not suffered any health shock (the "control" group). Our estimates suggest that, in our UK representative sample, there is no evidence that risk tolerance is significantly affected by past health shocks. Furthermore, the lack of association between shocks and risk tolerance is robust across all elicitation methods, experimental or self-reported, and across a number of further robustness checks.

Classification:

Keywords: health shocks; panel data; risk preferences; risk attitudes

JEL: I12; C23; D91

Contents of chapter 2

1. Introduction

A key and unresolved issue in empirical economics is whether risk tolerance is a stable individual trait; and whether and how it changes due to personal events. Traditional economic theory has built on the assumption that risk tolerance is stable across time (Stigler and Becker (1977)). Direct empirical evidence to date is mixed on this point. For example, Chuang and Schechter (2015), Galizzi et al. (2016a), and Schildberg-Hörisch (2018) provide recent reviews of the empirical studies testing the temporal stability of risk tolerance, and find mixed evidence[63].

In particular, and quite surprisingly, very little is known about the impact of past health shocks on risk tolerance. A number of recent studies, discussed in Section II and summarized in Table 1, have specifically explored the relationship between health shocks and risk tolerance in OECD countries, yielding mixed results to date. Two studies find a positive and significant association between health shocks and risk tolerance: individuals facing health shocks are less risk tolerant than those who do not face such shocks (Schurer (2015); Decker and Schmitz (2016)). One study finds a negative and significant association between health shocks and risk tolerance: health shocks lead to an increase in risk tolerance (Jones et al. (2018)). One last study finds a statistically non-significant relationship between health shocks and risk tolerance (Sahm (2012)). As Table 1 in Section II shows, methods differ greatly between studies, in terms of subject pool, of type of health shocks, and of the measurement of risk tolerance. These differences might explain the mixed nature of results. For example, and importantly, no study to date has looked at the impact of health shocks on risk tolerance when the latter is measured using experimental tasks with real monetary payments, rather than hypothetical questions or self-reported attitudes.

Our study contributes to this literature by systematically examining whether health shocks impact risk tolerance when the latter is measured by three different incentive-compatible experimental lottery games, and by three self-reported questions on willingness to take risks. To the best of our knowledge, this study is the first to systematically report the impact of health shocks on such a comprehensive set of measures for risk tolerance. Furthermore, by using a representative sample of the UK population, we are able to draw

[63] See for example in Chuang and Schechter (2015) and Galizzi et al. (2016a)

conclusions that are valid for the whole population.

We use the Innovation Panel (IP) of the UK Household Longitudinal Study[64] (UKHLS). The IP includes measures of risk tolerance whose full details can be found in Galizzi et al. (2016a). Risk tolerance is measured using both incentive-compatible experimental tests for risk preferences, and self-reported Likert-scale questions for risk attitudes. In particular, risk preferences are measured with three incentive-compatible experimental tasks: two multiple price list (MPL) binary lotteries tasks (Holt and Laury (2002)), one with low and one with high monetary stakes; and one ordered lottery task ((Binswanger, 1980; Binswanger et al., 1981); Eckel and Grossman (2008b)). Risk attitudes are measured with three self-reported questions on willingness to take risk in general, in health, and in finance (Dohmen et al. (2005)).

The set of experimental tasks allows Galizzi et al. (2016a) to estimate the individual risk aversion under standard Expected Utility Theory (EUT) and Constant Relative Risk Aversion (CRRA) assumptions. In particular, Galizzi et al. (2016a) use maximum likelihood to estimate the expected value of the individual relative risk aversion parameter, conditional on observable characteristics and on the choices in the experimental tasks. All their maximum likelihood estimations account for the complex survey design by using appropriate sampling weights to draw valid inference for the adult population in the UK, and adjust standard errors at cluster and primary sampling unit levels.

In this study we reconstruct the past health shock history of each respondent using longitudinal information collected annually by UKHLS. Following Coile and Milligan (2009) and, more recently, Jones et al. (2018), we distinguish between acute and chronic health shocks, the former being proxied by heart diseases, stroke and cancer episodes, and the latter by diabetes, epilepsy, and mental health problems. We then systematically look at the links between past health shocks and individual risk tolerance as measured in terms of both experimental tests for risk preferences and self-reported risk attitudes.

In particular, we use propensity score matching (PS) to identify the causal effect of health shocks on risk tolerance. We estimate the propensity score of suffering a health shock using a probit model and time-invariant or pre-determined demographic and socioeconomic variables which are unaffected by the health shocks (e.g. gender, nationality, age, individual

[64]See more on: https://www.understandingsociety.ac.uk/about.

level of education, whether parents were working during adolescence, parents' nationality). The respondents in the "treatment" group, that is, those who have suffered a health shock, are then matched, based on this propensity score, with the individuals who have not suffered any health shock (the "control" group).

Our empirical results find no evidence that risk tolerance is affected by past health shocks, whether chronic or acute. Further, the lack of association between shocks and risk tolerance is robust across all elicitation methods, both experimental and self-reported, and across a number of further robustness checks. The only notable exception is for the self-reported willingness to take risks in general, which is marginally and positively associated with past health shocks. This last finding confirms that incentive-compatible experimental tasks to elicit risk preferences and hypothetical questions about self-reported risk attitudes may capture quite different dimensions and aspects of individual risk tolerance (e.g. Crosetto and Filippin (2016); Galizzi et al. (2016a); Brañas-Garza et al. (2018)).

The rest of the paper proceeds as follows. Section II briefly discusses the previous literature. Section III describes data and provides some descriptive statistics. Section IV presents our empirical strategy. Section V reports the results and the effectiveness of the identification strategy through robustness checks. The last section concludes the paper.

2. Background literature

Table 1 reports all the existing studies investigating the links between health shocks and risk tolerance in OECD countries. We specifically focused on these countries for three reasons. First, the type of health shocks differs greatly between OECD countries (e.g. cancers or cardiovascular diseases) and non-OECD countries (e.g. HIV or malaria infection; or loss of weight). Second, cultural dimensions of risk tolerance may vary between OECD and non-OECD countries making comparisons less accurate. Third, the availability of public and private insurance coverage can interfere with both the probability to face a health shock and with risk tolerance in OECD countries. This might be less prominent in non-OECD countries. The reader can refer to Chuang and Schechter (2015) and Gloede et al. (2015) for analogous reviews in developing countries.

Sahm (2012) uses data on 18,625 hypothetical-gamble responses from 12,003 individuals between ages 45 and 70 from a non-representative sample from the Health and Retirement Survey, and finds that only a very modest decline in risk tolerance over a window of 10 years. Major life events, measured with the diagnosis of a serious health conditions (i.e. heart attack, stroke, cancer, or lung disease), have little impact on the gamble responses. She concludes that risk preferences vary mainly across, but not within, individuals. One raison why Sahm (2012) does not find significant effects may be that because the sample is restricted to a population aged between 45 and 70 that is followed up from employment until retirement, while individuals change in risk tolerance may still be possible before the age of 45 or after 70, for example.

Schurer (2015) investigates which socioeconomic groups are most likely to change their risk attitude after facing an important health event (i.e. depression, and high blood pressure) using data from a nationally representative sample in Germany. Using seven years of the German Socio-economic panel (G-SOEP) and 36,105 individuals, she finds that the level of risk attitude remains fairly stable between depressed individuals and non-depressed individuals. However, Schurer (2015) finds that individuals diagnosed with high blood pressures are more risk averse than healthy individuals at age 35-45, while other age groups have not significant differences. These results might not be interpreted as causal. Selection bias could apply here: those that suffer from a health shock might be a specific group, different from those without health shocks. Reverse causality might be an additional source of concern: risk attitudes may be determining the individual probability of health shocks.

Like Schurer (2015), Decker and Schmitz (2016) also use the G-SOEP to assess whether a health shock (i.e. change in individual grip strength (GS) over time[65]) influence risk attitude. Their approach enhance the one of Schurer (2015) by using a regression-adjusted matching approach which allows for a more causal interpretation of the results. Using a sample of 6,642 individuals observed during 9 waves, Decker and Schmitz (2016)find that a health shock significantly increases individual risk aversion. More precisely, a health shock leads to a decrease of about 9-11% of a standard deviation in the risk attitude of individuals. Such results persist until at least four years after the occurrence of the shock.

[65]More precisely they calculate the following ratio: ((Grip Strength$_t$ - Grip Strength$_{t-2}$)/(Grip Strength$_{t-2}$)).

More recently, Jones et al. (2018) investigate whether the effect of health shock on financial risk attitudes differs by personality traits. They distinguish between two sets of health conditions: acute (i.e. cancer, stroke, and heart problems) and chronic (i.e. lung problem, diabetes, high blood pressure, arthritis, and psychological problems) health shocks. Personality traits are measured on the basis of 26 personality questions that are then aggregated to have an indicator similar to the Big-Five index (i.e. in terms of neuroticism, extroversion, agreeableness, contentiousness, and openness to experience). Outcome variables are the stock market participation (whether or not the household holds stocks or bonds) and the percentage of risky assets in the portfolio (ratio of stocks and bonds to total financial wealth). Using 11 waves of the United States Health and Retirement Study, they find that extrovert individuals are more risk tolerant than others after facing such health shocks.

Table 1 : Summary of existing studies on the relationship between health shocks and risk tolerance

Study	Health shock measure	Risk tolerance measure	Method	Country	Results
Sahm (2012)	Heart attack, stroke, cancer, or lung disease	Hypothetical gamble questions	Maximum-likelihood method	US	No relationship
Schurer (2015)	Depression, and high blood pressure	Self-reported general risk attitude	Linear random effects model and a bivariate kernel regression	Germany	Less risk tolerant
Decker and Schmitz (2016)	Change in individual grip strength	Self-reported general risk attitude	Regression-adjusted matching	Germany	Less risk tolerant
Jones et al. (2018)	Acute and chronic	Self-reported financial risk attitude	Probit and tobit model	US	Extrovert individuals are more risk tolerant

3. Data

UKHLS is the largest multi-topic, nationally representative household panel survey in the world, interviewing annually more than 40,000 respondents[66]. It includes an Innovation Panel (IP), a parallel longitudinal, nationally representative, survey of about 1,500 households, whose questionnaire content mirrors that of the larger survey but which was designed for pre-testing of questions and for experimental and methodological studies (Jackle et al. (2018)). A

[66]UKHLS is funded by the Economic and Social Research Council (ESRC) and managed by the Institute for Social and Economic Research at the University of Essex. The individual data on risk tolerance have been collected by the project “Linking Experimental and Survey Data: Behavioural Experiments in Health” funded by the ESRC (ES/K001965/1, PI: MM Galizzi).

total of 661 respondents in the IP completed the risk preferences module in wave 6 (i.e. IP6), and 468 did it again one year later, in wave 7 (i.e. IP7). A total of 413 individuals answered the risk preferences questions in both IP 6 and IP 7. In designing the risk tolerance questions, a number of considerations and constraints were taken into account, the most pressing being the need to keep the overall burden of the experimental module low in order to minimize respondents' fatigue, non-response, and attrition. Full detail of the research strategy, the sampling, and the experimental design can be found in Galizzi et al. (2016a).

3.1. Variables of interest

The same sample of respondents answered three different experimental tasks with real monetary rewards to measure risk preferences and three self-reported questions on risk attitudes. All the tasks and questions are described in full detail in Galizzi et al. (2016a).

In a nutshell, subjects responded to two multiple price list (MPL) binary lotteries tasks (Holt and Laury (2002)), one with low monetary stakes (*HL Low*) and one with high monetary stakes (*HL High*). Each task consisted of a series of nine binary questions, where subjects had to choose between two risky lotteries, lottery A and lottery B. Lottery B was "riskier" than lottery A, in the sense that its two possible monetary outcomes were more spread apart from each other, with one very high monetary prize but also with one very low prize, each occurring with some different probabilities. The series of questions varied the probabilities of winning the high prize payment in the two lotteries. Typically, subjects prefer lottery A for low probabilities of the high prize payment, but then "switch" to preferring lottery B when such a probability is sufficiently high. The point in the series of questions where a respondent switches from preferring lottery A to preferring lottery B can be used to infer their risk aversion. In particular, under standard assumptions of Expected Utility Theory (EUT) and Constant Relative Risk Aversion (CRRA), one can associate a range of values of risk aversion to each question in which the respondent switches from preferring lottery A to lottery B (Table 2). Section IV.a on the empirical strategy illustrates how we estimate the individual risk aversion based on the choices in the *HL Low* and *HL high* tasks. Hereafter *HL Low* and *HL High* refer to the individual level of risk aversion as estimated based on the corresponding tasks.

Table 2: HL lottery probabilities, payoffs, expected values, and corresponding CRRA ranges

HL Low

Lottery A				Lottery B				CRRA Range	
P	GBP	(1-p)	GBP	P	GBP	(1-p)	GBP	Lower bound	Upper bound
0.1	40	0.9	32	0.1	77	0.9	2	$-\infty$	-1.71
0.2	40	0.8	32	0.2	77	0.8	2	-1.71	-0.95
0.3	40	0.7	32	0.3	77	0.7	2	-0.95	-0.49
0.4	40	0.6	32	0.4	77	0.6	2	-0.49	-0.14
0.5	40	0.5	32	0.5	77	0.5	2	-0.14	0.15
0.6	40	0.4	32	0.6	77	0.4	2	0.15	0.41
0.7	40	0.3	32	0.7	77	0.3	2	0.41	0.68
0.8	40	0.2	32	0.8	77	0.2	2	0.68	0.97
0.9	40	0.1	32	0.9	77	0.1	2	0.97	1.37

HL High

Lottery A				Lottery B				CRRA Range	
P	GBP	(1-p)	GBP	P	GBP	(1-p)	GBP	Lower bound	Upper bound
0.1	100	0.9	40	0.1	180	0.9	2	$-\infty$	-0.75
0.2	100	0.8	40	0.2	180	0.8	2	-0.75	-0.32
0.3	100	0.7	40	0.3	180	0.7	2	-0.32	-0.05
0.4	100	0.6	40	0.4	180	0.6	2	-0.05	0.16
0.5	100	0.5	40	0.5	180	0.5	2	0.16	0.34
0.6	100	0.4	40	0.6	180	0.4	2	0.34	0.52
0.7	100	0.3	40	0.7	180	0.3	2	0.52	0.70
0.8	100	0.2	40	0.8	180	0.2	2	0.70	0.91
0.9	100	0.1	40	0.9	180	0.1	2	0.91	1.20

The same subjects also responded to an ordered lottery task ((Binswanger, 1980; Binswanger et al., 1981); Eckel and Grossman (2008b); *B-EG*). The task required the subjects to choose among six lotteries with a fifty percent chance of receiving either a low or a high monetary prize. One lottery was a safe bet (lottery A, with a variance of 0), whereas the other five lotteries entailed increasing levels of variance, and thus of risk. In particular, under standard EUT and CRRA assumptions, the choice of each lottery can be associated to a corresponding range of risk aversion (Table 3). Section IV.a on the empirical strategy illustrates how we estimate the individual risk aversion based on the choice in the *B-EG* task. Hereafter *B-EG* refers to the individual level of risk aversion as estimated based on the corresponding task.

Table 3: *B-EG* lottery probabilities, payoffs, expected values, and corresponding CRRA ranges

Choice	Payoff				CRRA Ranges	
	Low	High	Expected return	Standard deviation	Lower bound	Upper bound
A	28	28	28	0	3.36	$+\infty$
B	24	36	30	8.5	1.16	3.46
C	20	44	32	17	0.71	1.16
D	16	52	34	25.5	0.499	0.71
E	12	60	36	33.9	0	0.499
F	2	70	36	48.1	$-\infty$	0

Note: participants have to choose only one lottery among the six lotteries.

The same subjects then answered three questions also included in the German SOEP survey (Dohmen et al. (2005)) about self-reported attitude towards risk-taking in general (*SOEP-G*), in health (*SOEP-H*), and in finance (*SOEP-F*), each taking values from 0 ("I am generally a person unwilling to take risks) to 10 ("I am generally a person fully prepared to take risks).

Looking at different measure of risk tolerance is important because risk taking is likely to be a multifaceted and largely context-specific construct (e.g. Loewenstein et al. (2001); Weber et al. (2002); Blais and Weber (2006); Prosser and Wittenberg (2007); Galizzi et al. (2016b)). Moreover, the evidence to date is mixed on the extent to which different measures correlate and map into each other (see Galizzi et al. (2016a) for a summary of the evidence of the cross-validity or convergent validity of different measures of risk tolerance).

The first measure is an experimental elicitation task for risk preferences over real monetary payment developed by Holt and Laury (2002) (HL). We used one with high payoff, and another one with low payoff. This procedure has the advantage of being directly related to the constant relative risk aversion (CRRA) function, and is supposed to measure the underlying risk preferences of an individual. One disadvantage of this measure is that is not easy to understand, and not context specific.

The second measure is an experimental elicitation task for risk preference over real monetary payment developed by Binswanger (1980); Binswanger et al. (1981) and applied by Eckel and Grossman (2008a), Eckel and Grossman (2008b) (B-EG). It involves a choice between six lotteries with different level of risk. We select this measure because it has the advantage of being simple to understand, intuitive, and easily understandable whatever the individual level of education. This also has the advantage of leading to consistent choices (Charness and Viceisza (2015)). The disadvantages of this measure is that it does not allow to discriminate between different degrees of risk seeking and maps into a limited range of CRRA parameters that do not directly overlap with the range of risk aversion imply by the reference version of the Holt and Laury (2002) lotteries.

The third measure of is a self-reported question for general, health and finance risk attitudes on a 10 points-Likert scale developed by Dohmen et al. (2011). This has the advantage of being a context-specific question (e.g. Loewenstein et al. (2001), Blais and Weber (2006)), and very easy to understand. Theses questions have, however, some drawbacks: it could suffer from desirability bias and from anchorage bias, and also because the procedure does not allow to associate the different individual choices with specific ranges of risk aversion parameters under the CRRA framework.

Despite the multiple of methods to elicit risk preferences in lab and/or in field settings, a relatively limited number of studies have directly looked at how these different measures correlate and map into each other, and the vast majority of these studies have considered student samples.

To measure the health shock, we rely on a question asking about the onset of a chronic or an acute health shock. The initial question was: “has a doctor or other health professionals ever told you that you have any of the conditions listed on this card?" Subjects could then select from a list of conditions. These conditions could be: congestive heart failure, coronary heart disease, heart attack or myocardial infarction, stroke, cancer or malignancy, diabetes, epilepsy, or clinical depression. Respondents also had to report the year, or the age, at which such disease was first diagnosed. Further they could also report if they were still living with the mentioned disease. We therefore have information on the type of shock (chronic or acute), the time elapsed since diagnosis, and their current disease status.

Our measure of health shocks includes the following conditions: heart diseases, heart failures, heart attacks, cancers, diabetes, epilepsy, and depression. Even though the arthritis and stroke are conditions that were asked in the question survey, we did not include such conditions in the analysis as no individuals reported having them.

The above-mentioned conditions are categorized into two groups: acute and chronic health shocks. Acute health shocks refer to conditions that indicate immediate serious health threats. Such is the case for heart diseases, heart failures, heart attacks and cancers. Comparatively, the other conditions are considered to be more chronic, suggesting ongoing problems that may be serious but which are perhaps less of an immediate health threat. Such is the case for diabetes, epilepsy, and depression.

By doing so, we are adopting the categorization made by a number of health economists (e.g. McClellan (1998); Fan and Zhao (2009); Coile and Milligan (2009); Love and Smith (2010); Sahm (2012); Jones et al. (2018)).

Such questions were asked from wave 1 to wave 7. We are thus able to reconstruct and document the entire past health history of an individual in the IP. From Tables 4 and 5, it can be seen that there are 192 individuals in the IP who faced a health shock. In particular, 93 (48.4% of the sample) individuals faced an acute health shock, and 99 (51.6% of the sample) a chronic health shock. More precisely, 16 (8.3% of the sample) individuals faced a heart disease, 21 (10.9% of the sample) a heart failure, 21 (10/9% of the sample) a heart attack, 35 (18.2% of the sample) a cancer, 34 (17.7% of the sample) have diabetes, 5 (2.6% of the sample) have an epilepsy issue, and 51 (26.5% of the sample) have depression. Most of them still lived with their disease, as only 23 individuals (21% of the sample) mentioned a finishing date[67].

[67]We have, however, no information on the reasons why individuals have a finishing date.

Table 4: Acute health shocks history

Heart disease			Heart failure			Heart attack			Cancer		
Start	End	n	Start	End	n	Start	End	n	Start	End	n
1970	/	1	1956	/	1	1998	/	1	1959	/	1
											1
											1
1992	/	1	1980	2010	1	.	.	20	1981	2012	1
1993	/	1	1982	/	1				1982	2008	1
1995	/	1	1988	/	2				1987	2008	1
1998	/	1	1990	2010	1				1989	2009	1
2003	/	1	1992	/	1				1993	2008	1
2007	2010	1	1995	/	1				1994	2009	1
2008	2010	1	1999	/	1				1998	2008	1
.	.	8	2000	/	1				2002	2008	1
			2001	/	1				2003	2009	1
			2003	2009	1				2003	2008	1
			2004	2011	1				2003	/	1
			2004	2010	1				2004	2008	1
			2004	/	1				2005	2008	1
			2007	/	1				2006	2008	1
			2009	2010	1				2006	2009	1
			2009	/	3				2007	2009	1
		. .			1				2008	/	1
											17
		16			21			21			35

Note: (/) indicates that the disease is still ongoing and (.) indicates missing information.

Table 5: Chronic health shocks history

Diabetes			Epilepsy			Depression		
Start	End	n	Start	End	n	Start	End	n
1963	/	1	1979	2008	1	1956	2008	1
1974	/	1	1983	/	1	1965	2009	1
1975	/	1	1997	2008	1	1966	2008	1
1978	/	1	1998	/	1	1968	2008	1
1987	/	2	.	.	1	1972	/	1
1998	/	1				1974	2008	1
1999	/	2				1984	/	1
2001	/	2				1989	/	2
2003	/	2				1991	/	1
2004	/	3				1992	/	1
2005	/	1				1993	/	2
2006	/	2				1994	/	5
2008	2008	1				1995	/	1
2008	/	2				1996	/	1
2009	/	1				1998	2008	1
.	.	20				1998	/	1
						2000	2008	1
						2002	2013	1
						2003	2008	1
						2005	2009	2
						2005	2008	1
						2006	2008	1
						2007	2008	2
						2007	/ 1	
						2008	2008	1
						2008	/	2
						2009	/	2
						.	.	13
		43			5			51

Note: (/) indicates that the disease is still ongoing and (.) indicates missing information.

We also use demographic and socioeconomic variables for our propensity score, summarized in the following table (Table 6). We choose these variables to because they are variables which are pre-determined at the time of the health shocks. The choice of such covariates is of the uttermost importance as they represent a set of potential confounders. Theoretically, we should include in our PS all variables that correlate both with the probability to face a health shock and with risk tolerance (this is discussed in greater details in Section IV, and, in particular, in sub-section IV.c). Furthermore, our matching covariates should have not been impacted by health shocks. To ensure that this is not the case, we rely on time-invariant variables that are recorded in the UKHLS waves before the occurrence of the health shocks. Other important confounders, such as income or employment status, are not included among our PS variables as they are available and provided only in the same waves (IP6 or IP7) of the data collection of the risk tolerance variables. We therefore have no certainty on whether or not such variables have been impacted by the health shocks.

Table 6: variables used for the propensity score

Names	Measured by	Description
Age	Continuous variable	From 16 to 94 years old
Gender	Dummy variable	1 if respondent is a female, 0 otherwise
Educational attainment	Dummy variable	1 if respondent has at least an upper secondary school degree, 0 otherwise
Mother working status during childhood	Dummy variable	1 if respondent is working, 0 otherwise
Father working status during childhood	Dummy variable	1 if respondent is working, 0 otherwise
Mother nationality	Dummy variable	1 if respondent is from United-Kingdom, 0 otherwise
Father nationality	Dummy variable	1 if respondent is from United-Kingdom, 0 otherwise

3.2. Descriptive statistics

A nationally representative sample of 661 individuals in the IP answered risk tolerance questions in IP6, and 468 answered them in IP7. A total of 413 individuals responded to the same questions in both IP6 and IP7.

From our initial sample we first excluded a subset of the respondents who gave "strongly inconsistent" responses to the risk tolerance questions. It is generally assumed that respondents should be consistent with their choices, that is, once in the sequence of HL questions they have chosen lottery B, they should not choose lottery A in any of the following other questions. They should not, therefore, switch back to option A once they have previously chosen lottery B (and vice-versa). A common finding in the lab and field experiments that do not impose consistency in individual responses is that a notable proportion of subjects make such inconsistent responses. For example, Crosetto and Filippin (2016) find that 16.3% of respondents make inconsistent choices, and Charness and Viceisza (2015) find that such rate could rank from 14% to 66.5%.

Some of this "switching back" behavior can be easily rationalized in our conceptual framework by considering larger intervals for the CRRA. For example, if the respondents choose lottery B at some point, switch back to lottery A, and then choose lottery B again, we can simply construct a larger interval of CRRA values where the lower bound of the interval is calculated in correspondence of the first point where respondents choose lottery B, and the higher bound of the interval is calculated in correspondence of the last point where they choose lottery B. However, if respondents choose lottery B at some point, switch back to lottery A, and never choose lottery B again, we are not able to estimate their CRRA because their choices cannot be associated to any bounded interval of he CRRA. Therefore, we call the latter type of respondents "strongly inconsistent" and we simply exclude them from the analysis.

Our responses are not an exception to this general finding. More precisely, due to strongly inconsistent responses, our sample size in IP6 reduces to 569 individuals for *HL Low*, 586 for *HL High*, 653 for *B-EG*, 603 for *SOEP-G*, and 602 for both *SOEP-F* and *SOEP-H*. In IP7 the sample size reduces to 362 for *HL Low*, 393 for *HL High*, to 451 for *B-EG*, to 431 for *SOEP-G*, and to 430 for *SOEP-F* and *SOEP-H*.

In IP7 the corresponding sample size reduces to 362 for *HL Low*, 393 for *HL High*, 451 for *B-EG*, to 431 for *SOEP-G*, and to 430 for *SOEP-F* and *SOEP-H*.

Among the 569 observations for *HL Low* in IP6, a total of 124 individuals have faced a health shock whereas 445 individuals have not faced any health shock. However, two strata are omitted because they contain no sub-population members, which leaves us with 122 individuals that face such health shocks. We therefore have 567 observations for *HL Low* in IP6.

We proceed in the same manner for all our outcome variables, and so have the following sample sizes: 585 individuals for *HL High* (138 had a health shock – but 1 stratum omitted – and 448 do not have such a shock); 652 for *B-EG* (146 had a health shock – but 1 stratum omitted – and 507 does not have such a shock); 602 for *SOEP-G* (132 had a health shock – but 1 stratum omitted – and 471 does not have such a shock); 601 for *SOEP-H* (132 had a health shock – but 1 stratum omitted – and 470 does not have such a shock); 601 for *SOEP-F* (132 had a health shock – but 1 stratum omitted – and 470 does not have such a shock).

In IP7, we have 359 individuals for *HL Low* (90 had a health shock - but 1 stratum omitted – and 272 do not have such a shock); 390 for *HL High* (92 had a health shock - but 1 stratum omitted – and 301 do not have such a shock); 448 for *B-EG* (106 had a health shock - but 1 stratum omitted – and 345 do not have such a shock); 428 for *SOEP-G* (102 had a health shock - but 1 stratum omitted – and 329 do not have such a shock – but 2 strata are omitted); 427 for *SOEP-F* and *SOEP-H* (101 had a health shock - but 1 stratum omitted – and 329 do not have such a shock – but 2 strata are omitted)[68].

Table 7 reports the descriptive statistics for the whole sample in each wave (IP6 and IP7) and divided between the groups of individuals who faced or did not face health shocks.

Descriptive statistics show that there are generally no significant differences in risk tolerance measures between the groups of respondents in our sample who have faced health shocks and the ones who have not face health shocks. Two notable exceptions refer to i) the self-reported willingness to take risks in general that, in both IP6 and IP7, is significantly higher in respondents who faced health shocks; ii) the HL measures of risk aversion in IP7 that indicate higher risk aversion for individuals who have faced health shocks based on both *HL Low* and *HL High*. The fact that, according to descriptive statistics, respondents who faced health shocks simultaneously manifest both higher risk tolerance (according to the *SOEP-G*) and lower risk tolerance (according to *HL Low* and *HL High*) is puzzling, and in fact we will get back to this point later.

However, descriptive statistics also show that individuals in our sample who faced heath shocks have different characteristics from individuals in our sample who have not faced health shocks. For instance, on average the individuals who have faced health shock were

[68] When considering the respondents who answer the risk tolerance questions in both IP6 and IP7, we have 349 individuals for *HL Low* (79 had a health shock - but 4 strata omitted – and 276 do not have such a shock - but 2 strata omitted); 356 for *HL High* (87 had a health shock - but 5 strata omitted – and 276 do not have such a shock - but 2 strata omitted); 399 for *B-EG* (94 had a health shock - but 5 strata omitted – and 312 do not have such a shock - but 2 strata omitted); 379 for *SOEP-G* (85 had a health shock - but 5 strata omitted – and 293 do not have such a shock - but 3 strata omitted); 378 for *SOEP-F* and *SOEP-H* (85 had a health shock - but 5 strata omitted – and 293 do not have such a shock - but 4 strata omitted).

significantly older than the group of individuals who have not face health shocks (59 years old on average, compared to 47), and also had a lower educational attainment. These differences occur in both wave IP6 and wave IP7. More descriptive statistics can be found in Table 6 for the two groups and for the two different waves. These underlying differences in the two groups calls for a quasi-experimental empirical strategy to take into account the non-randomness of the shocks.

Table 7: descriptive statistics by groups and by waves

	Wave 6 (661)			Wave 7 (468)		
Variables	Health Shocks	No Health Shock	Obs.	Health Shocks	No Health Shock	Obs.
HL Low	-0.152	-0.075	567	0.251	-0.230	359
	(0.198)	(0.114)	(0.292)	(0.135)		
HL High	0.120	0.094	585	0.302	0.055	390
	(0.173)	(0.080)	(0.231)	(0.076)		
B-EG	2.119	1.937	652	2.056	2.139	448
	(0.262)	(0.121)	(0.356)	(0.156)		
SOEP-G	5.926	5.410	602	5.911	5.240	428
	(0.350)	(0.142)	(0.231)	(0.189)		
SOEP-H	6.897	6.892	601	6.987	6.941	427
	(0.250)	(0.130)	(0.407)	(0.181)		
SOEP-F	6.922	6.809	601	7.000	6.923	427
	(0.352)	(0.119)	(0.376)	(0.206)		
Female	0.483	0.540	660	0.505	0.535	455
	(0.046)	(0.022)	(0.068)	(0.030)		
Education	0.337	0.442	660 0.367	0.463	463	
	(0.053)	(0.032)	(0.067)	(0.034)		
Age	58.468	46.771	660	56.011	48.015	468
	(2.604)	(1.090)	(3.832)	(1.294)		
Father working	0.859	0.887	640	0.863	0.892	450
	(0.035)	(0.017)	(0.055)	(0.018)		
Mother working	0.536	0.602	639	0.572	0.642	449
	(0.050)	(0.026)	(0.069)	(0.025)		
Father from UK	0.751	0.749	379	0.733	0.724	264
	(0.056)	(0.039)	(0.085)	(0.046)		
Mother from UK	0.751	0.749	379 0.784	0.729	264	
	(0.056)	(0.039)	(0.073)	(0.041)		

this table shows the differences in mean of all covariates and outcomes variables between the treated and the control group (columns 3 and 6). Descriptive statistics are calculated using sampling weights. Standard errors are adjusted to account for strata and PSU in the survey.

Table 8 shows the descriptive statistics for the subsample of individuals who provided risk tolerance measures in both IP6 and IP7. As it can be seen, the statistics are closely comparable to the ones illustrated above for the entire samples of all respondents to IP6 and IP7. This provides direct evidence that attrition was not a substantial issue here.

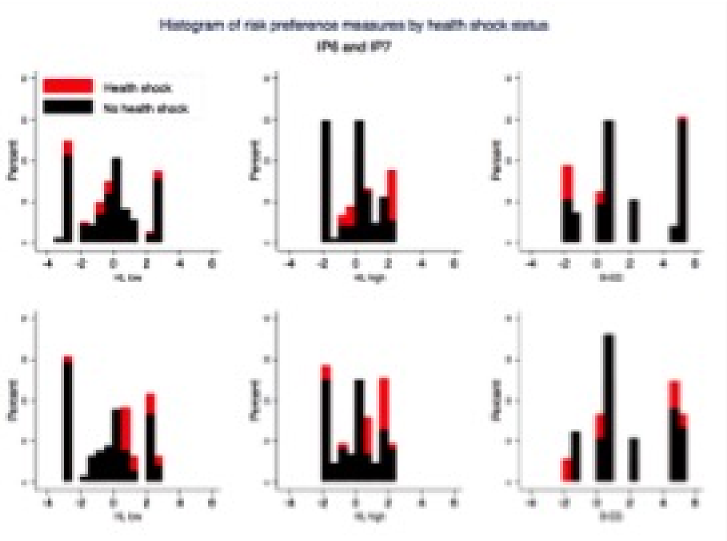
Table 8: descriptive statistics of groups if individuals are both in wave 6 and 7

	IP 6 and 7 (413)		
Variables	Health Shocks	No Health Shock	Obs.
HL Low	0.009	-0.130	349
	(0.419)	(0.136)	
HL High	0.161	0.144	356
	(0.291)	(0.097)	
B-EG	2.573	1.971	399
	(0.321)	(0.189)	
SOEP-G	5.726	5.221	371
	(0.417)	(0.183)	
SOEP-H	6.568	6.677	370
	(0.354)	(0.171)	
SOEP-F	6.940	6.667	370
	(0.396)	(0.158)	
Female	0.526	0.542	404
	(0.077)	(0.039)	
Education	0.366	0.506	404
	(0.080)	(0.041)	
Age	55.648	45.280	404
	(4.792)	(1.504)	
Father working	0.874	0.891	394
	(0.084)	(0.025)	
Mother working	0.628	0.647	393
	(0.092)	(0.034)	
Father England	0.701	0.739	237
	(0.083)	(0.047)	
Mother England	0.743	0.737	237
	(0.067)	(0.045)	

this table shows the differences in mean of all covariates and outcomes variables between the treated and the control group (columns 3 and 6). Descriptive statistics are calculated using sampling weights. Standard errors are adjusted to account for strata and PSU in the survey.

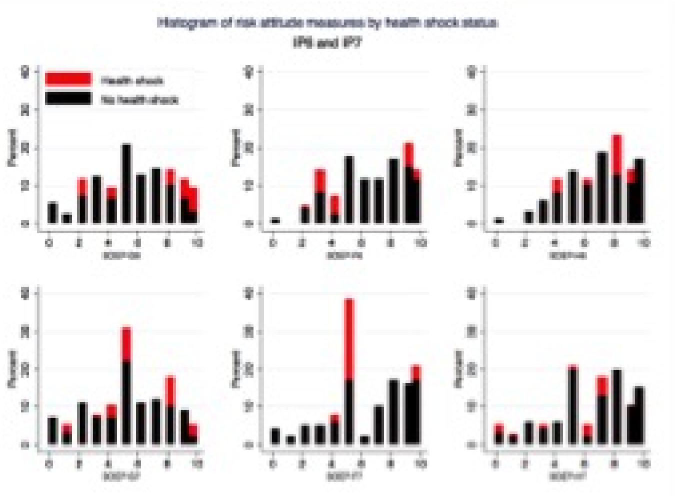
Figures 1 and 2 provides, respectively, the distribution of the experimental and non-experimental measures of risk tolerance among the individuals who took part to both IP6 and IP7 measurements and who have faced or not faced health shocks. No clear pattern emerges for IP6. For IP7 individuals who have faced health shocks seem to have lower risk tolerance (higher risk aversion) than those who have not faced health shocks when risk tolerance is measured by the *HL Low* or the *HL High* tasks. For risk attitudes, no clear differences exist between our two groups in IP6. In IP7, however, it seems that individuals who have faced health shocks are more likely to report higher scores for *SOEP-G* and *SOEP-F*. Not so clear pattern emerges for *SOEP-H*.

Figure 1: Distributions of risk preferences for respondents who have faced or not faced health shocks



Note: The x-axis refers to the risk preference measure, and the y-axis refers to the proportion of respondents. The histograms used sampling weights.

Figure 2: Distributions of risk attitudes for respondents who have faced or not faced health shocks



Note: The x-axis refers to the risk attitude measures, and the y-axis refers to the proportion of respondents. The histograms used sampling weights.

4. Empirical strategy

4.1. Estimation of risk preferences

We look at the links between past health shocks and risk aversion (CRRA). Our estimates of risk aversion are directly based on Galizzi et al. (2016a). In their estimations, Galizzi et al. (2016a) exploit the theoretical links between the observed lottery choices in the *HL Low*, *HL High*, and *B-EG* experimental tasks and the bounds of relative risk aversion intervals consistent with the EUT and CRRA assumptions reported in Tables 2 and 3 (like in Loomes and Pogrebna (2014); Crosetto and Filippin (2016)). In particular, Galizzi et al. (2016a) use standard interval regression models to estimate the latent relative risk aversion r_i, of the individual i, with r_i, a linear function of observable (x_i) and unobservable (ϵ_i) individual characteristics, i.e. $r_i = x_i'\beta + \epsilon_i$, and the observed choice y_i is determined by:

$$y_i = \begin{cases} 1 & \text{si } x_i'\beta + \epsilon_i \leq r_{u1} \\ 2 & \text{si } r_{u1} \leq x_i'\beta + \epsilon_i \leq r_{u2} \\ . & \dots \\ K & \text{si } r_{uK-1} \leq x_i'\beta + \epsilon_i \end{cases}$$

Where $1, 2, \ldots, K$ are the available choices in the experimental tasks (i.e. the switching points in the *HL Low* and *HL High* tasks and the lotteries in the *B-EG* task); and r_{u1}, $r_{u2}, \ldots, r_{uK}$ are the upper bounds of the sets of relative risk aversion parameters consistent with the choices $1, 2, \ldots, K$, respectively (see Tables 2 and 3). In the case of the *HL Low* and *HL High* tasks, Galizzi et al. (2016a) focus on the subset of participants whose choices can be plausibly rationalized within a EUT and CRRA theoretical framework, that is, they exclude from the estimation sample those "inconsistent" subjects who, after having chosen lottery B "switch back" to lottery A in a way that cannot be associated to any bounded interval of CRRA values[69].

Galizzi et al. (2016a) assume the random component ϵ_i to be independent from the observable characteristics x_i, identically and normally distributed, $\epsilon_i | x_i$ iid N(0, σ2), and we estimate β and σ via maximum likelihood (ML). The ML estimations account for the complex survey design by using appropriate sampling weights to draw valid inference for the adult population in the UK, and adjust standard errors at strata and PSU levels.

Here we use the individually estimated CRRA values as the main dependent variables in the comparison between respondents who faced health shocks and matched respondents who did not face health shocks.

For the SOEP questions, the answers cannot be rationalized in a EUT and CRRA framework, and therefore here we simply use ordered probit (OP) estimations to model the choices in the 0-10 Likert scales. In particular, the dependent variable can take 11 values, associated with the 11 degrees of risk tolerance that the subject self-reported.

4.2. Design of matching

We aim at estimating the impact of health shocks on risk tolerance. Yet, as seen from the descriptive statistics, individuals who have faced health shocks may have different characteristics from respondents who have not faced health shocks. Further, individuals who

[69] The choices of some of the "inconsistent" subjects, in fact, can be easily managed by an interval regression model once we allow for behavioural "mistakes" in the sequence of choices. For example, if a subject switches to lottery B, then "switches back" to lottery A, and then switches to lottery B again and always chooses lottery B thereafter, his choices can be accommodated using a wide range of rra values whose lower bound coincides with the lower bound of the interval implied by the first switching point from lottery A to B, and the upper bound is given by the upper bound of the last switching point. See Galizzi et al. (2016a) for more on the "inconsistent" subjects.

have faced health shocks may also have different lifestyle choices (e.g. may smoke and drink more, eat less healthily) and different genetic characteristics (e.g. inherited genes associated with increased risks of cancer or diabetes). Therefore, the likelihood that individuals face health shocks is not exogenous.

In order to take into account the non-randomness of the occurrence of such shocks, we rely on PS matching, a quasi-experimental method (Rosenbaum and Rubin (1983); (Pearl, 2000; Pearl et al., 2009); Ho et al. (2007); and Garrido et al. (2014)). The propensity score is the probability that a given individual participates in the treatment conditional on his or her observed characteristics. The propensity score is a balancing score: conditional on the propensity score, the distribution of measured baseline covariates is similar between the "treated" individuals (i.e. individuals who have faced health shocks) and the "control" individuals (i.e. individuals who have not faced health shocks). Thus, in a set of individuals whom have the same PS, the distribution of observed characteristics is the same between the treated and the control individuals. Ideally, all variables that influence both the probability of experiencing a shock and the measures of risk tolerance should be observable and included in the PS. Furthermore, to properly estimate the effect of the shock, one needs to have, for each value of the PS, both a treated unit and a control unit.

The PS matching consists in calculating the average difference between the mean outcome of the treated individuals characterized by a specific PS, and the mean outcome of the control individuals characterized by a similar PS. The PS matching implies pairing each treated individual with comparable control individuals. Specifically, we calculate the matched outcomes (Y_j^{PSM}) using the weighted outcomes of the 3-nearest-neighbors (j[70]) of a treated individual i:

$$Y_j^{PSM} = \sum w_{ij} Y_j \tag{1}$$

Where w_{ij} is the weight of control individual j, with $\sum w_{ij} = 1$, and Y_j stands for the outcome of control individual j before the matching. Thus, the average effect of the health shock (AEHS) is given by:

[70] Here j refers to the number of control matched, in our case, j=3 as we are implementing a 3-nearest neighbor matching.

$$AEHS = 1/N \sum (Y_i - Y_j^{PSM}) \tag{2}$$

Where N is the number of treated individuals in the sample for whom a matched control individual exists.

For our matching to be valid, the selection must be ideally based solely on observable characteristics, and all the variables that influence both treatment assignment (i.e. experiencing health shocks) and outcomes (i.e. risk tolerance) must also be observed. In practice, however, this is unlikely to be the case.

Further, the choice of the nearest neighbors is bounded to the common support range[71]. We calibrate the maximum difference in the propensity score between matched and control subjects to be at 0.1[72]. This ensures that matched individuals have very similar propensity scores. Our matching is also performed with replacement[73], which implies that the same control individual can be used as a nearest neighbor for more than a single treated individual.

4.3. Implementation of matching

To compute the PS, we first estimate a probit model (Wooldridge et al. (2000); Imbens and Wooldridge (2009); and Lechner et al. (2011)), which contains the variables described in Section III (age, gender, educational attainment, mother and father working status during individuals' childhood, individuals' mother and father nationality).The expected relationships between matching variables and the treatment assignment and the outcome variable are detailed below.

Older individuals (especially the 55-74 age group) are more likely to face health shocks[74] and are also more risk averse (e.g. Riley Jr and Chow (1992); (Bellante and Green, 2004); Gollier (2008)). Men are more likely to have a heart attack or a heart failure than women

[71] Treatment observations with propensity scores higher than the maximum, or less than the minimum, propensity score of the controls are discarded.

[72] This means, for example, that a treated individual with a propensity score of 0.6 is matched with an individual in the control group with a propensity score of 0.5 or 0.7.

[73] Replacement increases the average quality of the matching, because treated individuals are more likely to be matched with a control individual with the same PS, thereby decreasing the bias. However, allowing replacement also reduces the number of distinct controls used to construct the counterfactual outcomes, and therefore, increases the variance of the estimator (Smith and Todd (2005)).

[74] See more on the following websites: https://www.cancer.gov/about-cancer/causes-prevention/risk/age;https://www.diabetes.org.uk/resources-s3/2017-11/diabetes_in_the_uk_2010.pdf; and https://www.mentalhealth.org.uk/statistics/mental-health-statistics-older-people.

(e.g. Weidner (2000); Appelman et al. (2015)). Women are, however, more likely to be risk averse than men (e.g. (Holt and Laury, 2002); Hartog et al. (2002); (Dohmen et al., 2005); Croson and Gneezy (2009); Charness and Viceisza (2015)). Individuals with higher level of educational attainment are, on average, in better health (e.g. Adams (2002); Arendt (2005)), and are also more likely to be risk averse (Hammitt and Haninger (2010); (Kandel et al., 2009)). Individuals with parents of different nationality matter for health: migration worsens children health (e.g. (Stillman et al., 2012)), which in turn, impacts adulthood health (e.g. Sawyer et al. (2012)) It also impact the risk tolerance as migrants and their children are more risk tolerant than individuals who do not choose to migrate (e.g. Akguc et al. (2016)). Finally, children with unemployed parents have worse health in childhood (e.g. (Pieters and Rawlings, 2016)) and have higher willingness to take risks in their future life (e.g. (Hryshko et al., 2016)).

Among our matching variables, gender, educational attainment, and age are available for all individuals (n=661) in IP6. We also have information on the respondents' mother and father working status during their childhood for respectively 640 and 641 respondents in IP6, and on mother and father nationality for 382 of them. We, therefore, have a complete PS for 382 individuals in IP6. Gender, educational attainment, and age are available for all individuals (n=468) in IP7 as well. We also have information on respondents' mother and father working status during their childhood for respectively 453 and 454 respondents in IP7, and on mother and father nationality for 269 of them. We, therefore, have a complete PS for 269 individuals in IP7[75].

Additionally, for some respondents we do have a complete PS, but no information on risk tolerance (or vice-versa). More precisely, in IP6 we have a complete PS for 382 individuals, but no information on *HL Low* for 55 individuals that lead to a sample size of 327 individuals. By applying a similar argument for each of our outcome variables, we get the following sample sizes: 342 individuals for *HL High*, 380 for *B-EG*, and 343 for *SOEP-G*, *SOEP-F*, and *SOEP-H*. In IP7, we have a complete PS for 269 individuals, but no information on *HL Low* for 57 individuals that lead to a sample size of 212 individuals. By applying a similar argument

[75]Gender, educational attainment, and age are available also for all the individuals (n=468) who respond to both IP6 and IP7. We also have information on respondents' mother and father working status during their childhood for respectively 401 and 402 respondents in both IP6 and IP7, and on mother and father nationality for 244 of them. We, therefore, have a complete PS for 244 individuals who responded to both IP6 and IP7

for each of our outcome variables, we get the following sample sizes: 223 for *HL High*, 261 for *B-EG*, 248 for *SOEP-G*, 247 for *SOEP-F* and *SOEP-H*. For individuals that are present in both IP6 and IP7, we have a complete PS for 244 individuals, but no information on *HL Low* for 38 individuals in IP6 that lead to a sample size of 206 individuals, and 46 in IP7 that lead to a sample size of 198. For the other outcome variables we have a sample size of 216 and 207 for *HL High*, 244 and 237 for *B-EG*, 221 and 229 for the *SOEP-G*, 221 and 228 for the *SOEP-F* and *SOEP-H*.

4.4. Matching quality

This subsection assesses the quality of our matching strategy. To assess the quality of the implemented matching procedure, we compare several indicators before and after the matching and we check if any differences remain after conditioning on the PS.

First, we address the concern that our PS includes variables that are not significant in the Probit estimation (see more in Table A in the appendix). We follow Rubin and Thomas (1996) and Augurzky and Kluve (2007) who suggest that the inclusion of non-significant variables would not bias the estimates. They recommend excluding such variables only if there is a consensus that they are unrelated to the outcome[76]. We share the view that non-significant variables should be included in the PS because they are indeed related to the outcomes (as mentioned in section IV.c).

Second, we address the concern that the mean of the variables included in the PS may be significantly different for the treatment and control group (Rosenbaum and Rubin (1983)). Table 10 reports that before matching, substantial and statistically significant differences in some variables (e.g. gender, educational attainment, and age) exist between the treatment and the control groups. After matching, none of these differences are statistically significant at any conventional levels. The treatment and the control groups are, therefore, on average similar.

[76]See Bryson et al. (2002) for a discussion of the pros and cons of this approach.

Table 10: Assessing matching quality

Variables	Before matching			After matching			
	Treatment group	Control group	Difference before matching	Treatment group	Control group	Difference before matching	Reduction bias
Father working	0.876	0.902	-0.026	0.876	0.862	0.014	46.6%
Mother working	0.505	0.592	-0.087	0.505	0.526	-0.021	76.2%
Father UK	0.742	0.792	-0.050	0.742	0.739	0.003	93.1%
Mother UK	0.742	0.775	-0.033	0.742	0.770	-0.028	17.3%
Education	0.299	0.424	-0.125**	0.299	0.302	0.003	97.3%
Gender	0.474	0.612	-0.138**	0.474	0.522	-0.048	65.1%
Age	58.688	50.814	7.874***	58.688	57.526	1.162	85.2%
R2	0.086			0.005			
Rubin'B	72.9			16.3			
Rubin'R	1.05			1.53			

Note: Rubin's B is the absolute standardized difference of the means of the linear index of the propensity score in the treated and (matched) non-treated group. Rubin's R is the ratio of treated to (matched) non-treated variances of the propensity score index.

Third, although variables could be on average identical after matching, some disparities may still exist in their distribution. For instance, age is on average the same after matching, but distributions may not overlap as the treatment group has a 1.638 standard deviation, and the control group has 0.920. We use the standardized bias indicator in order to make the distribution of covariates more equal after matching. The standardized bias indicator is defined as the difference of the sample means in the treated and matched control as a percentage of the square root of the average sample variances in both group[77] (Rubin (2001); Lechner (2002); Sianesi (2004); Caliendo and Kopeinig (2008)). Table 8 shows in greater detail the resulting reduction in variance. All variables' biases are reduced from 17.3% to 97.3% (where a 100% reduction would imply that after matching the biases have entirely disappeared).

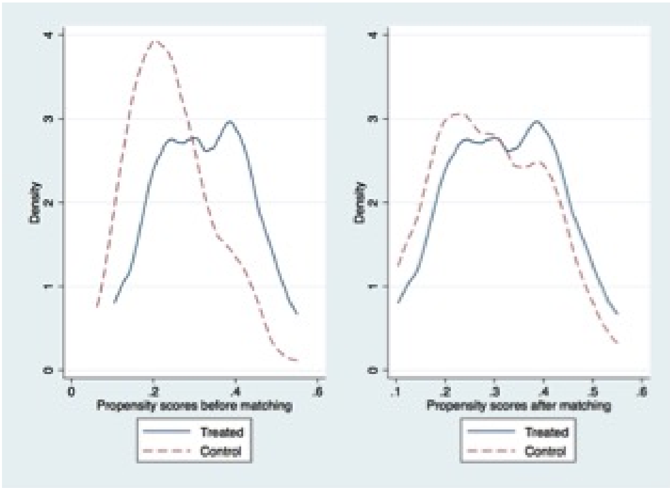
Fourth, we provide information as to how well the regressors explain the probability to have a shock. After matching, there should be no systematic differences in the distribution of covariates, and the matched Pseudo-R^2 should therefore be lower than the unmatched Pseudo-R2 (Sianesi (2004); Caliendo and Kopeinig (2008)). Further, following Rubin (2001), we test the similarity of the covariate distributions using the two following statistics. First, the absolute standardized difference of the means of the propensity score between the treated and matched control group (Rubin's B). Second, the ratio of the variance of the propensity scores of the treated and the matched control (Rubin's R). The samples are usually said to

[77] $SB_{before} = (X_1 - X_0)/(\sqrt{(0.5(V_1(X) - V_0(X))}$ and $SB_{after} = (X_{1M} - X_{0M})/(\sqrt{(0.5(V_{1M}(X) - V_{0M}(X))}$.

be sufficiently balanced when the first statistic is smaller than 25%, and the second statistic is between 0.5 and 2 (Rubin, 2001). These are the case in our sample as the Rubin's B is equal to 16.3 and the Rubin's R is equal to 1.57. These could also be seen and checked in Table 10.

Fifth, in Figure 3, we display the distribution of the PS for the treated (continuous line) and control (dashed line) individuals before (left-hand side), and after (right-hand side) the matching procedure. While some overlap in the distribution is visible before matching, post-matching distributions exhibit a clearly better fit.

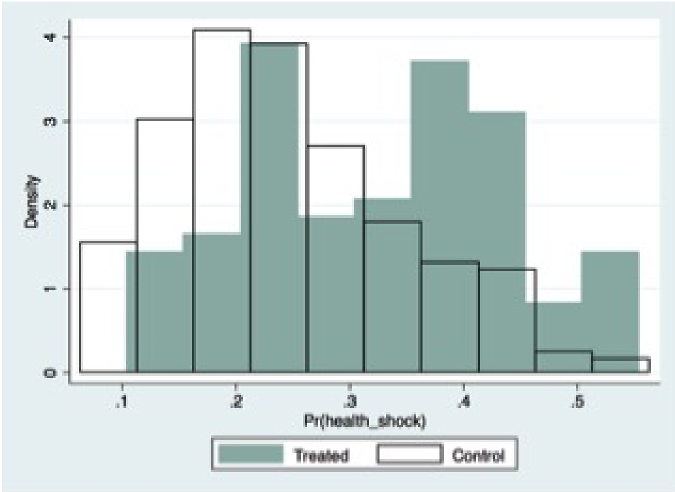
Figure 3: Distributions of PS before and after the matching among groups.



Note: We plot the distributions of the PS and their estimated density among the treated and the control group before (left-hand side) and after (right-hand side) the matching. The x-axis refers to the PS and ranges from 0 to 1; the y-axis refers to its estimated density. The estimated density that a treated individual face a health shock has most of its mass near to 0.2 before the matching. The treatment group looks more similar to the estimated density of the control group after the matching.

Figure 4 displays the region of the common support to ensure that the overlap between both groups is sufficient to make comparisons. The histogram displays the PS for the treatment and control cases. Control and treated individuals span the full range of the PS, which gives further support to our empirical strategy.

Figure 4: Distribution of PS among groups



Note: the x-axis refers to the PS and ranges from 0 to 1, the y-axis refers to its estimated density. The treated group is represented in full-color, while the control group is represented in transparent-color. The estimated density that a treated individual face a health shock has most of its mass near to 0.2, and 0.4, while it is from 0.1 to 0.3 for an individual in the control group.

Sixth, matching with few variables has some strength. First, if the number of matching variables increases, it becomes difficult to find units that are adequately similar on all dimensions (e.g. Roberts et al. (2015)). Second, as we are mostly using dummy matching variables (6 over 7 are dummies), we reduce difficulty to match on high-dimensional data. Further, optimal matching is more likely to occur when using low-dimensional setting (e.g. Hainmueller and Xu (2013); Diamond and Sekhon (2013); Imai and Ratkovic (2014)).

For all these specifications, we find a high degree of similarity between the treatment and control group. Despite of these specifications, uncertainty remains. First, we do not observe all potential confounders and that the PS does not take into account self-selection of riskier individuals into the treatment group. Among potential confounders, lifestyle variables (e.g. cigarette consumption, alcohol consumption, practicing physical activities), income, and type of employment (e.g. self-employed) may be the most important as they all are related with the probability to face health shocks and with risky behaviors. Additionally, we would have benefit from using the two waves of risk tolerance measures avalaible, but this was not possible due to limited sample size.

5. Results

5.1. Main results

Table 11 shows the impact of health shocks on the different measures of risk tolerance in IP6 using the PS matching approach presented in Section IV. We report results as follows. Column 1 provides the effect of health shocks on *HL Low*, column 2 for *HL High*, column 3 for *B-EG*, column 4, 5 and 6 for *SOEP-G*, *SOEP-F*, and *SOEP-H*, respectively. The empirical results show no evidence that risk tolerance is significantly affected by health shocks. Further, once the matching is implemented to account for underlying differences in the two groups, the lack of association between shocks and risk tolerance is robust across all the elicitation methods, both experimental and self-reported.

As we use a 3 nearest neighbors (3NN) matching and impose that all individuals satisfy the underlying assumptions (explained in detail in Section IV.b), which explained why we lose some observations for each measure of risk tolerance. More precisely, the propensity score is computed for each measure of risk tolerance. Therefore, for IP6 we have 327 individuals for whom we have information on *HL Low*, 342 individuals for whom we have information on *HL High*, 380 individuals for whom we have information on *B-EG*, 343 individuals for whom we have information on *SOEP-G*, *SOEP-F*, and *SOEP-H*. In IP7, we have 212 individuals for whom we have information on *HL Low*, 223 for whom we have information on *HL High*, 261 for whom we have information on *B-EG*, 248 for whom we have information on *SOEP-G*, and 247 for whom we have information on both *SOEP-F* and *SOEP-H*[78].

Table 11: Impact of health shock on risk tolerance in IP6

	HL Low	*HL High*	*B-EG*	*SOEP-G*	*SOEP-F*	*SOEP-H*
	(1)	(2)	(3)	(4)	(5)	(6)
Health Shock	-0.090	-0.075	-0.151	0.288	-0.037	-0.195
	(0.296)	(0.195)	(0.357)	(0.348)	(0.331)	(0.345)
Observations	327	342	380	343	343	343

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[78]For individuals answering both in IP6 and IP7, the number of observations falls to 206 for *HL Low*, 216 for *HL High*, 244 for *B-EG*, 221 for *SOEP-G*, *SOEP-F* and *SOEP-H* (in IP6) ; to 198 for *HL Low*, 207 for *HL high*, 229 for *SOEP-G*, 228 for *SOEP-F* and *SOEP-H* (in IP7).

Table 12 documents the impact of health shocks on measures of risk tolerance in IP7. Results are consistent with those of Table 11. The only notable exception is for the self-reported willingness to take risks in general, which is marginally significantly associated with past health shocks. Incidentally, *SOEP-G* also shows a positive sign (although only marginally significant).

Table 12: Impact of health shock on risk tolerance in IP7

	HL Low	*HL High*	*B-EG*	*SOEP-G*	*SOEP-F*	*SOEP-H*
	(1)	(2)	(3)	(4)	(5)	(6)
Health Shock	0.325	0.022	-0.424	0.831*	0.625	0.208
	(0.341)	(0.232)	(0.396)	(0.433)	(0.421)	(0.439)
Observations	212	223	261	248	247	247

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 13 shows the impact of health shocks using individuals that responded to both IP6 and IP7. Results corroborate those of Tables 11 and 12. That is, there is no effect of health shocks on risk tolerance, with the exception of *SOEP-G* and *SOEP-F* in IP7 that show, again, positive signs.

Table 13: Impact of health shock on risk tolerance in IP6 and IP7

	IP 6						IP 7					
	HL Low	*HL High*	*B-EG*	*SOEP-G*	*SOEP-F*	*SOEP-H*	*HL Low*	*HL High*	*BE-G*	*SOEP-G*	*SOEP-F*	*SOEP-H*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Health Shock	-0.209	-0.199	0. 475	0.581	0.282	0.036	0.330	0.150	-0.642	1 217***	0.940**	0. 474
	(0.374)	(0.245)	(0.459)	(0.432)	(0.405)	(0.433)	(0.358)	(0.241)	(0.427)	(0.456)	(0.447)	(0.477)
Observations	206	216	244	221	221	221	198	207	237	229	228	228

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.2. Robustness checks

Two robustness checks were performed to assess the sensitivity of our results to the matching strategy, by testing alternative types of matching techniques.

First, we use a radius matching approach (Dehejia and Wahba (2002)), which includes not only the nearest neighbors within the caliper, but also all comparison members within the caliper. Using a 0.1 radius, an individual in the treatment group is thus matched with all individuals in the control group with a propensity score within a 0.1 difference. By using all comparison individuals available within the radius, it extends the number of units for which good matches are available, thereby reducing the risk of bad matches. Columns 1 to 6 in Tables 14, 15 and 16 show that results using Radius matching have the same magnitude as those from the initial matching, and remain statistically not significant, with the exception of the *SOEP-H* measure which is marginally significantly (and positively) associated with past health shocks[79].

Table 14: Robustness checks of the effect of health shock on risk tolerance (IP6)

	IP 6						IP 7					
	HL Low	*HL High*	*B-EG*	*SOEP-F*	*SOEP-F*	*SOEP-H*	*HL Low*	*HL High*	*B-EG*	*SOEP-G*	*SOEP-F*	*SOEP-H*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Health Shock	-0.025	-0.081	-0.114	0.357*	0.087	-0.041	-0.021	-0.070	-0.052	0.281	0.034	-0.082
	(0.260)	(0.170)	(0.305)	(0.300)	(0.287)	(0.289)	(0.267)	(0.175)	(.314)	(0.309)	(0.295)	(0.298)
Observations	327	342	380	343	433	343	327	342	380	343	343	343

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Second, we implement a Kernel matching (Heckman et al. (1997); Heckman et al. (1998)). This is a non-parametric matching estimator using weighted averages of all individuals in the control group to construct the counterfactual outcomes. In this case, an individual in the treatment group is matched with all individuals in the control group, and the control individuals who are closer to the treated individual are given higher weights. One major advantage of this approach is that it reduces the variance of the estimates as more information is used. Columns 7 to 12 in Tables 14, 15 and 16 show results for Kernel matching.

Table 15: Robustness checks of the effect of health shock on risk tolerance (IP7)

	Radius matching						Kernel matching					
	HL Low	*HL High*	*B-EG*	*SOEP-G*	*SOEP-F*	*SOEP-H*	*HL Low*	*HL High*	*B-EG*	*SOEP-G*	*SOEP-F*	*SOEP-H*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Health Shock	0.401	0.107	-0.460	0.812***	0.375	0.268	0.393	0.124	-0.520	0.795***	0.447	0.248
	(0.307)	(0.206)	(0.349)	(0.375)	(0.360)	(O.384)	(0.313)	(0.209)	(0.355)	(0.385)	(0.370)	(0.392)
Observations	212	223	261	248	247	247	212	223	261	248	247	247

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[79]For all our robustness checks, the numbers of observations are the same as those used in the Section V.a

Tables 14 and 15 document the fact that there is no effect of health shocks on risk tolerance when we use individuals present in both waves. Table 16 provides the robustness checks of our PS matching using the radius matching, and Table 17 provides the same specification but for the Kernel matching.

Table 16: Robustness checks of the effect of health shock on risk tolerance (IP6 and IP7)

	Radius matching											
	IP 6						IP 7					
	HL Low	*HL High*	*B-EG*	*SOEP-G*	*SOEP-F*	*SOEP-H*	*HL Low*	*HL High*	*B-EG*	*SOEP-G*	*SOEP-J*	*SOEP-H*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Health Shock	-0.008	-0.052	0.121	0.423	0.300	0.054	0.406	0.194	-0.507	1.063 ***	0.563	0.355
	(0.333)	(0.215)	(0.399)	(0.375)	(0.365)	(0.375)	(0.322)	(0.215)	(0.368)	(0.399)	(0.382)	(0.418)
Observations	211	216	244	221	221	221	198	207	237	229	228	228

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 17: Robustness checks of the effect of health shock on risk tolerance (IP6 and IP7)

	Kernel matching											
	IP 6						IP 7					
	HL Low	*HL High*	*B-EG*	*SOEP-G*	*SOEP-F*	*SOEP-H*	*HL Low*	*HL High*	*B-EG*	*SOEP-G*	*SOEP-F*	*SOEP-H*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Health Shock	-0.084	-0.112	0.198	0.487	0.407	0.120	0.367	0.242	-0.607	1.087 ***	0.753*	0.361
	(0.344)	(0.226)	(0.415)	(0.390)	(0.379)	(0.390)	(0.333)	(0.220)	(0.381)	(0.415)	(0.398)	(0.433)
Observations	206	216	244	221	221	221	198	207	237	229	228	228

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Overall, our results are robust to these two alternative matching strategies, which indicates that the health shocks do not impact risk tolerance, which the only exception of the self-reported attitude to take risks in general.

6. Conclusion

This study is the first to date to systematically and transparently report the impact of health shocks on a range of different measures of risk tolerance which include both experimental and self-reported measures. Furthermore, it is unique in doing so for a representative sample of the UK population.

Our main finding is that, once a matching design is implemented in order to appropriately account for underlying differences between the respondents who have faced and who have never faced health shocks, there is no evidence that risk tolerance is significantly affected by health shocks. Furthermore, the lack of association between shocks and risk tolerance is robust across all the elicitation methods, both experimental and self-reported ones, and across a number of further robustness checks.

Our study has several limitations. First, because our findings are derived from a UK representative sample, they may not directly generalize to other countries, settings, or samples. Second, our results do not control for non-cognitive skills (e.g. conscientiousness, extraversion) that can influence both the likelihood to face a shock and risk tolerance.

Further research is needed to systematically assess the impact of shocks on risk tolerance and other behavioral characteristics in representative samples of the population.

7. Appendix

Table A: Probit estimation for wave 6[80]

Variables	Probit estimation
	(1)
Father working	0.015
	(0.223)
Mother working	0.085
	(0.141)
Father england	-0.164
	(0.249)
Mother england	-0.046
	(0.247)
Female	-0.265*
	(0.137)
Education	-0.105
	(0.151)
Age	0.019***
	(0.004)
Constant	-1.396***
	(0.381)
Observations	407

Note: this Table provides the Probit estimation described in section III.
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

[80] Probit estimations of other waves are available on request.

Chapter 3

Thumbs down to the digit-ratio: 2D:4D does not predict risk tolerance nor time discounting in a UK representative sample

This chapter was co-authored
with **Matteo M. Galizzi** and **Sara Machado**.

Summary of the chapter:

We systematically investigate the links between the digit ratio (2D:4D), risk tolerance, and time discounting in a UK representative sample. The 2D:4D is a biomarker for prenatal testosterone exposure. We analyse two sets of measures for risk tolerance. The first set measures risk preferences as subjects choose between incentive-compatible monetary lotteries. The second set measures self-reported risk attitudes using Likert-scales questions. Furthermore, we measure time discounting using incentive-compatible experimental choices between Smaller-Sooner and Larger-Later monetary amounts. Finally, we investigate whether the digit ratio explains sex differences in risk tolerance and time discounting. We find no statistically significant association between the digit ratio, risk tolerance, and time discounting. We find no significant interaction between digit ratio and sex in explaining risk tolerance and time discounting.

Classification:

Keywords: risk preferences; risk attitudes; time discounting; biomarkers

JEL: D90; I12

Contents of chapter 3

1. Introduction

In this paper, we systematically investigate the relationships between the digit ratio, risk tolerance and time discounting in a UK representative sample. Furthermore, we investigate whether the digit ratio explains sex differences in risk tolerance and time discounting.

Our study focuses on an economic behavior that is often said to be sexually dimorphic: risk tolerance. Women are found to be, in general, more risk averse than men (e.g. Byrnes et al. (1999); Croson and Gneezy (2009)). Although social and cultural expectations for risk tolerance differ greatly between women and men, biological differences between sexes could play an important role in these behavior differences.

One important biological difference between men and women involves the hormone testosterone. Higher levels of testosterone in males can result in gender differences in behaviors and cognition through the organizational and activation effects of this hormone. The former refers to permanent modification of the brain structure during prenatal and early life due to exposure to testosterone. The latter refers to the transient effects of circulating testosterone on the brain during puberty (Knickmeyer et al. (2006)).

Testosterone has been show to correlate with various behaviors: it enhances the motivation of competition and dominance (Archer (2006)), reduces fear (van Honk et al. (2004); Hermans et al. (2006)), and it is associated with gambling, alcohol use (Dabbs Jr and Morris (1990); Mazur and Booth (1998); Blanco et al. (2001)), and with risk tolerance (Sapienza et al. (2009); Apicella et al. (2008); Stenstrom et al. (2011)).

In this chapter we investigate the organization effect of testosterone on risk tolerance by analyzing variation in prenatal testosterone exposure. In other words, we investigate whether differences in risk tolerance between genders can have its origin in prenatal androgen exposure.

Do to so, we use the 2D:4D digit ratio as a marker of prenatal testosterone exposure. Fingers have receptors for sex steroid hormones and their length is affected by hormone exposure *in-utero*. More specifically, the 2D:4D has been shown to be negatively correlated with prenatal testosterone exposure (Manning et al. (1998); McIntyre, 2006). This exposure reduces the growth of the second digit relative to the other fingers (Manning et al. (1998); Lutchmaya et al. (2004)). As a result, the second-to-fourth digit ratio has been used as a proxy of the exposure to prenatal testosterone (Manning et al. (2002); Manning et al. (2014)).

Our study, therefore, is of interest as it participates to the empirical debate on whether risk tolerance is – partly - determined before birth. Further it also provides a better understanding of the origin of gender differences in risk tolerance.

We use data from the Innovation Panel (IP) of the UK Household Longitudinal Study (UKHLS)[81] in particular from wave 6 (IP6)[82]. The IP includes measures of risk tolerance and time discounting whose full details can be found in Galizzi et al. (2016a). In particular, risk tolerance is measured using both incentive-compatible experimental tests for risk preferences (RP), and self-reported Likert-scale questions for risk attitudes (RA). The former set of experimental tasks allows us to estimate the individual risk aversion under standard Expected Utility Theory (EUT) and Constant Relative Risk Aversion (CRRA) assumptions. Time discounting (TD) is measured using a set of incentive-compatible experimental choices between Smaller-Sooner (SS) and Larger-Later (LL) monetary amounts.

Under EUT and CRRA assumptions, Galizzi et al. (2016a) use maximum likelihood to estimate the expected value of the individual CRRA parameter, conditional on observable characteristics and on the choices in the experimental tasks. Here we use a similar maximum likelihood approach to estimate the expected value of the individual implicit time discount rate (IDR), conditional on observable characteristics and on the choices in the SS-LL experimental tasks. All maximum likelihood estimations account for the complex survey design by using appropriate sampling weights to draw valid inference for the adult population in the UK, and adjust standard errors at cluster and primary sampling unit levels. We then use the individually estimated CRRA or IDR as the dependent variables in a set of linear regression models where the main explanatory variables are either the right-hand or the left-hand digit ratios (R2D:4D and L2D:4D, respectively), with and without a set of observable characteristics.

To the best of our knowledge, this is the first study to systematically link a broad range of measures of risk tolerance and time discounting with both the right-hand and the left-hand digit ratio using a representative sample of the population.

[81] See more on: https://www.understandingsociety.ac.uk/about.

[82] Results on IP7 can be found in the online appendix.

We find no statistically significant association between the digit ratio, risk tolerance, and time discounting. This lack of association is robust across all elicitation measures, and across a number of further robustness checks. Also, we find no significant interaction between digit ratio and sex in explaining risk tolerance and time discounting.

The rest of the paper is structured as follow. Section 2 summarizes the literature on digit ratio, risk tolerance and time discounting. Section 3 describes the data and presents the analysis method. Section 4 provides the results. Section 5 investigates whether sex differences in risk tolerance and time discounting can be explained by the digit ratio. The last section briefly discusses the main findings and concludes.

2. Background literature

This self-contained background section reports the previous evidence on the links between the digit ratio, risk tolerance, and time discounting.

Brañas-Garza et al. (2018) is the first study to systematically investigate the links between the digit ratio and different measures of risk tolerance. It does so by considering a large sample of LSE students from different ethnic backgrounds, the largest sample to date (n=704) where the digit ratio has been associated to measures of risk tolerance. It also does so by considering both hands' digit ratios, and both experimental and self-reported measures of risk tolerance. Brañas-Garza et al. (2018) find that both hands' digit ratios are significantly associated with risk preferences as measured by an incentive-compatible experimental task. Neither hand's digit ratio, however, is significantly associated with self-reported risk attitudes.

The present paper extends and generalizes the analysis of Brañas-Garza et al. (2018) in four different ways. First, we consider, for the first time ever, a representative sample of the population, rather than a convenience sample of university students. Second, we relate both hands' digit ratios not only to measures of risk tolerance, but also of time discounting, and we include two further experimental measures of risk preferences. Third, while we purportedly replicate the empirical analysis by Brañas-Garza et al. (2018) based on ordered probit models, we use maximum likelihood to estimate the expected value of the behavioural parameters for individual relative risk aversion and time discounting, under standard theoretical assumptions, and conditioning on the choices in the experimental tasks. Finally, we investigate whether the digit ratio explains sex differences in risk tolerance and time discounting.

Brañas-Garza et al. (2018) is also the first study to systematically report and critically discuss all the previous studies looking at the links between digit ratio and risk tolerance. None of the studies reported there (see their Table 1, for instance) considers a representative sample of the population: most studies there are based on convenience samples of students. Moreover, Brañas-Garza et al. (2018) find that five of those studies found that individuals with lower digit ratio are more risk tolerant (Brañas-Garza et al. (2018); Apicella et al. (2008); Garbarino et al. (2011); Ronay and von Hippel (2010); Brañas Garza and Rustichini (2011); Stenstrom et al. (2011)); whereas five other studies did not find any statistically significant association between the digit ratio and risk tolerance (Apicella et al. (2008); Sapienza et al. (2009); Aycinena and Rentschler (2018); Drichoutis and Nayga Jr (2015); Schipper (2014)).

Brañas-Garza et al. (2018) notice that such mixed results may be due the combination of small samples and selective sampling of specific ethnicities[83]. The above-mentioned studies, in fact, consider either samples of predominantly Caucasian subjects (Dreber and Hoffman (2007); Garbarino et al. (2011); Drichoutis and Nayga Jr (2015)) or relatively small sample of ethnically diverse subjects (Apicella et al. (2008); Sapienza et al. (2009); Schipper (2014); Drichoutis and Nayga Jr (2015)). Studies also differ in how the digit ratio is measured, ranging from photocopies and scanners to calliper or rulers. The actual digit ratio is defined by bone length, something that this is not directly observed in these studies. Any method that does not use radiographs potentially suffers from measurement bias. Moreover, these studies do not use the same digit ratio proxy: some used the digit ratio of both hands (Dreber and Hoffman (2007); Apicella et al. (2008); Aycinena and Rentschler (2018)), others used the mean digit ratio of the two hands (Sapienza et al. (2009); Ronay and von Hippel (2010); Garbarino et al. (2011);Stenstrom et al. (2011)), or the digit ratio of the right hand (Brañas Garza and Rustichini (2011); Schipper (2014); Drichoutis and Nayga Jr (2015)).

The literature is even more scant and mixed on the relationship between the digit ratio

[83]Ethnicity has been cited as an important source of variation in digit ratio: Manning et al. (2002) and Manning et al. (2014) report that the variation of digit ration between ethnic groups, and even between Caucasians of different European origin, is larger than the variation between sexes within an ethnic group. Such large variation makes it harder to detect a relationship between digit ration and risk taking in small sample.

and time discounting, with only five studies to date, all of which use the right-hand digit ratio only and consider convenience samples of students. Two studies use hypothetical tests and find a significant and negative association between the digit ratio and time discounting (Millet and Dewitte (2008); Takahashi et al. (2008)). The most recent three studies use incentive-compatible experimental tests to elicit individual discount rates: one finds no significant association (Drichoutis and Nayga Jr (2015)) whereas the other two studies find a negative significant association (Lucas and Koff (2010); Aycinena and Rentschler (2018)).

All the above-mentioned studies – investigating both the links between digit ratio and risk tolerance; and between digit ratio and time discounting – are summarized in Table 1.

Table 1: Summary of the existing studies on 2D:4D, risk tolerance, and time discounting

	Risk Tolerance		Time discounting		Characteristics			
Studies	Exp.	Money	Exp.	Money	Measure	Hands	Results	Representative
Brañas-Garza et al. (2018)	B-EG	Yes	No	No	Scanner	Both	(-)	No
Dreber and Hoffman (2007)	GP	Yes	No	No	Scanner	Both	(-)	No
Garbarino et al. (2011)	MLP	Yes	No	No	Scanner	Mean	(-)	No
Ronay and von Hippel (2010)	BART	Yes	No	No	Scanner	Mean	(-)	No
Brañas Garza and Rustichini (2011)	HL	No	No	No	Photocopy	Right	(-)	No
Stenstrom et al. (2011)	LTI	No	No	No	Calliper	Mean	(-)	No
Apicella et al. (2008)	GP	Yes	No	No	Scanner	Both	(-)	No
Sapienza et al. (2009)	HL	Yes	No	No	Scanner	Both	No	No
Aycinena and Rentschler (2018)	None	No	Yes	Yes	Scanner	Both	(-)	No
Lucas and Koff (2010)	None	None	Yes	Yes	Scanner	Both	No	No
Schipper (2014)	HL	Yes	No	No	Scanner	Right	No	No
Millet and Dewitte (2008)	No	No	No	Hypothetical reward	Scanner	Right	(-)	No
Takahashi et al. (2008)	No	No	No	Hypothetical reward	Scanner	Both	(-)	No

Note: Exp defines the type of experimental measure to elicit risk taking: B-EG refers to (?Binswanger et al., 1981); Eckel and Grossman (2008a); GP refers to the Gneezy-Potters test; MPL refer to multiple price list tests; BART refers to the Balloon Analog Risk Task. Mean refers to the mean of left and right 2D:4D. Hands refer to the digit ratio measure reported in the study. (-) means a statistically significant negative association between the digit ratio and the outcome under consideration.

3. Data and experimental design

UKHLS is the largest multi-topic, nationally representative, household panel survey in the world, interviewing annually more than 40,000 respondents[84]. It includes an Innovation Panel

[84]UKHLS is funded by the Economic and Social Research Council (ESRC) and managed by the Institute for Social and Economic Research at the University of Essex. The individual data on risk tolerance and time discounting have been collected by the project "Linking Experimental and Survey Data: Behavioural Experiments in Health" funded by the ESRC (ES/K001965/1, PI: MM Galizzi).

(IP), a parallel longitudinal, nationally representative, survey of about 1,500 households, whose questionnaire content mirrors that of the larger survey but which has been designed for pre-testing of questions and for experimental and methodological studies (Jackle et al. (2013)).

A total of 661 respondents in the IP6 completed a behavioural economics module containing experimental tasks and self-reported questions for risk tolerance and time discounting (Galizzi et al. (2016a)). In designing the module, a number of considerations and constraints were taken into account, the most pressing being the need to keep the overall burden of the experimental module low in order to minimize respondents' fatigue, non-response, and attrition. Full detail of the research strategy, the sampling, and the experimental design can be found in Galizzi et al. (2016a).

3.1. Digit ratio

The digit ratio in IP6 has been measured using a digital Vernier Caliper. This has been done in a face-to-face interview where the lengths of the ring and index fingers of both hands have been measured by the professional interviewers. This reduces measurement error, as respondents did not have to directly report their digit ratios using proxies[85].

3.2. Risk tolerance measures

The same sample of respondents answered three different experimental tasks with real monetary rewards to measure risk preferences and three self-reported questions on risk attitudes. All the tasks and questions are described in full detail in Galizzi et al. (2016a).

In a nutshell, subjects responded to two multiple price list (MPL) binary lotteries tasks (Holt and Laury (2002)), one with low monetary stakes (HL Low) and one with high monetary stakes (HL High). Each task consisted of a series of nine binary questions, where subjects had to choose between two risky lotteries, lottery A and lottery B. Lottery B was "riskier" than lottery A, in the sense that its two possible monetary outcomes were more spread apart from each other, with one very high monetary prize but also with one very low prize, each occurring with some different probabilities. The series of questions varied the

[85] The procedure is described in detail at https://www.understandingsociety.ac.uk/documentation/innovation-panel/fieldwork-documents.

probabilities of winning the high prize payment in the two lotteries. Typically, subjects prefer lottery A for low probabilities of the high prize payment, but then "switch" to preferring lottery B when such a probability is sufficiently high. The point in the series of questions where a respondent switches from preferring lottery A to preferring lottery B can be used to infer their risk aversion. In particular, under standard assumptions of Expected Utility Theory (EUT) and Constant Relative Risk Aversion (CRRA), one can associate a range of values of risk aversion to each question in which the respondent switches from preferring lottery A to lottery B (Table 2). Section IV.a on the empirical strategy illustrates how Galizzi et al. (2016a) estimate the individual risk aversion based on the choices in the HL low and HL high tasks. Hereafter HL low and HL high refer to the individual level of risk aversion as estimated based on the corresponding tasks.

Table 2: HL lottery probabilities, payoffs, expected values, and corresponding CRRA ranges

HL Low

Lottery A				Lottery B				CRRA Range	
P	GBP	(1-p)	GBP	P	GBP	(1-p)	GBP	Lower bound	Upper bound
0.1	40	0.9	32	0.1	77	0.9	2	$-\infty$	-1.71
0.2	40	0.8	32	0.2	77	0.8	2	-1.71	-0.95
0.3	40	0.7	32	0.3	77	0.7	2	-0.95	-0.49
0.4	40	0.6	32	0.4	77	0.6	2	-0.49	-0.14
0.5	40	0.5	32	0.5	77	0.5	2	-0.14	0.15
0.6	40	0.4	32	0.6	77	0.4	2	0.15	0.41
0.7	40	0.3	32	0.7	77	0.3	2	0.41	0.68
0.8	40	0.2	32	0.8	77	0.2	2	0.68	0.97
0.9	40	0.1	32	0.9	77	0.1	2	0.97	1.37

HL High

Lottery A				Lottery B				CRRA Range	
P	GBP	(1-p)	GBP	P	GBP	(1-p)	GBP	Lower bound	Upper bound
0.1	100	0.9	40	0.1	180	0.9	2	$-\infty$	-0.75
0.2	100	0.8	40	0.2	180	0.8	2	-0.75	-0.32
0.3	100	0.7	40	0.3	180	0.7	2	-0.32	-0.05
0.4	100	0.6	40	0.4	180	0.6	2	-0.05	0.16
0.5	100	0.5	40	0.5	180	0.5	2	0.16	0.34
0.6	100	0.4	40	0.6	180	0.4	2	0.34	0.52
0.7	100	0.3	40	0.7	180	0.3	2	0.52	0.70
0.8	100	0.2	40	0.8	180	0.2	2	0.70	0.91
0.9	100	0.1	40	0.9	180	0.1	2	0.91	1.20

The same subjects also responded to an ordered lottery task ((?Binswanger et al., 1981); Eckel and Grossman (2008a); B-EG). The task required the subjects to choose among six lotteries with a fifty percent chance of receiving either a low or a high monetary prize. One lottery was a safe bet (lottery A, with a variance of 0), whereas the other five lotteries entailed increasing levels of variance, and thus of risk. In particular, under standard EUT and CRRA assumptions, the choice of each lottery can be associated to a corresponding range of risk aversion (Table 3). Section IV.a on the empirical strategy illustrates how Galizzi et al. (2016a) estimate the individual risk aversion based on the choice in the B-EG task. Hereafter B-EG refers to the individual level of risk aversion as estimated based on the corresponding task.

Table 3: B-EG lottery probabilities, payoffs, expected values, and corresponding CRRA ranges.

Choice	Payoff				CRRA Ranges	
	Low	High	Expected return	Standard deviation	Lower bound	Upper bound
A	28	28	28	0	3.36	$+\infty$
B	24	36	30	8.5	1.16	3.46
C	20	44	32	17	0.71	1.16
D	16	52	34	25.5	0.499	0.71
E	12	60	36	33.9	0	0.499
F	2	70	36	48.1	$-\infty$	0

The same subjects then answered three questions also included in the German SOEP survey (Dohmen et al. (2011)) about self-reported attitude towards risk-taking in general (SOEP-G), in health (SOEP-H), and in finance (SOEP-F), each taking values from 0 ("I am generally a person unwilling to take risks") to 10 ("I am generally a person fully prepared to take risks").

Looking at different measure of risk tolerance is important because risk taking is likely to be a multifaceted and largely context-specific construct (e.g. Slovic et al. (2004); Weber et al. (2002); Blais and Weber (2006); Prosser and Wittenberg (2007); Galizzi et al. (2016b)). Plus, the evidence to date is mixed on the extent to which different measures correlate and map into each other (see Galizzi et al. (2016a) for a summary of the evidence of the cross-validity or convergent validity of different measures of risk tolerance).

3.3. Time discounting measures

Respondents also had to choose between different Smaller Sooner (SS) and Larger Later (LL) options in order to measure their time discounting using incentive-compatible experimental tests. The same set of inter-temporal binary options was presented twice, one with Front End Delay (FED) and one without FED. In both FED and non-FED cases, questions were presented in blocks ordered according to three increasing time horizons occurring between the SS and the LL option: 1 month, 3 months, and 12 months. To make it easier for respondents to see the inter-temporal tradeoffs, in each block the list of questions was presented in increasing order of 12 LL amounts of money and implicit discount rates (Andersen et al. (2014)). This intuitively ordered design thus gave rise to a total number of 72 time preference questions: 12 (implicit discount rates: 5%, 10%, 15%, 20%, 25%, 30%, 40%, 50%, 60%, 80%, 100%, and 150% per year) x 3 (time horizons: 1 month, 3 months, 12 months) x 2 (front end delay: FED or no FED).

One single question was presented at a time in a separate screen. A block of 36 questions with FED were presented first. Within this FED block, a first sub-block of 12 questions (FED 1) presented a choice between a SS Option A involving a "principal" payment of £100 in 1 month, and a LL Option B within 1 month interval, that is, involving a larger monetary amount in 2 months. The 12 questions in the sub-block were constructed in a way that the LL option had annual implicit interest rates equal to 5%, 10%, 15%, 20%, 25%, 30%, 40%, 50%, 60%, 80%, 100%, and 150%. Amounts for the LL monetary values were calculated using simple, rather than compounded (e.g. bi-annually, quarterly), annualized discounting rates. This was done to ensure consistency with the standard practices and current regulations within the banking and financial sectors in the UK where, typically, interest rates for mortgages, bonds, and credit cards, are expressed as simple annualized rates.

The second sub-block of 12 FED questions used the same annual implicit discount rates but with 3-month time horizon (FED 3: 1 month in Option A versus 4 months in Option B), while the third sub-block of 12 FED questions used the same discount rates for a time interval of 12 months (FED 12: 1 month in Option A versus 13 months in Option B).

The non-FED block of 36 questions followed with the same 1 month, 3 months, and 12 month intervals, and the same implicit discount rates, but no FED (No-FED 1, No-FED 3, and No-FED 12, respectively).

The wording of the questions was the same in all the questions and it was: ”between Option A and Option B, which option do you prefer? Option A: receiving £100 in 1 month; Option B : Receiving £100.42 in 2 months.” A typical sample of questions is reported in Table 4 below.

Table 4: FED 1 block of questions on time discounting

Option A (in 1 month)	Option B (in 2 months)	Which option do you prefer?	
£100	£100.42	A	B
£100	£100.83	A	B
£100	£101.25	A	B
£100	£101.67	A	B
£100	£102.08	A	B
£100	£102.50	A	B
£100	£103.33	A	B
£100	£104.17	A	B
£100	£105.00	A	B
£100	£106.67	A	B
£100	£108.33	A	B
£100	£112.50	A	B

3.4. Control variable measures

We also exploit the richness of the UKHLS panel by using a broad set of control variables in our analysis. Such variables are summarized and described in Table 5.

Table 5: Description of the socio-demographic variables

Names	Measured with	Description
Age	Continuous variable	It ranges from 16 to 96
Income (log)	Continuous variable	It ranges from 2.82 to 12.71
Sex	Dummy variable	1 if respondent is a female, 0 otherwise
Marital status	Dummy variable	1 if respondent is in couple, 0 otherwise
Educational attainment	Dummy variable	1 if respondent has at least an upper secondary school degree, 0 otherwise
Being self-employed	Dummy variable	1 if respondent is self-employed, 0 otherwise
Being unemployed	Dummy variable	1 if respondent is unemployed, 0 otherwise
Being an employee	Dummy variable	1 if respondent is an employee, 0 otherwise

4. Empirical analysis

4.1. Estimation of risk aversion

We look at the links between digit ratios and risk aversion (CRRA). Our estimates of risk aversion are directly based on Galizzi et al. (2016a). In their estimations, Galizzi et al. (2016a) exploit the theoretical links between the observed lottery choices in the HL low, HL high, and B-EG tasks and the bounds of relative risk aversion intervals consistent with the EUT and CRRA assumptions reported in Tables 2 and 3 (like in Loomes and Pogrebna (2014); Filippin and Crosetto (2016)). In particular, Galizzi et al. (2016a) use standard interval regression models to estimate the latent relative risk aversion r_i, of the individual i, with r_i, a linear function of observable (x_i) and unobservable (i) individual characteristics, i.e. $r_i = x_i'\beta + \epsilon_i$, and the observed choice y_i determined by:

$$y_i = \begin{cases} 1 & \text{si } x_i'\beta + \epsilon_i \leq r_{u1} \\ 2 & \text{si } r_{u1} \leq x_i'\beta + \epsilon_i \leq r_{u2} \\ . & \dots \\ K & \text{si } r_{uK-1} \leq x_i'\beta + \epsilon_i \end{cases}$$

where $1, 2, \dots, K$ are the available choices in the experimental tasks (i.e. the switching points in the HL low and HL high tasks and the lotteries in the B-EG task); and $r_{u1}, r_{u2}, \dots, r_{uK}$ are the upper bounds of the sets of relative risk aversion parameters consistent with the choices $1, 2, \dots, K$, respectively (see Tables 2 and 3). In the case of the HL low and HL high tasks, Galizzi et al. (2016a) focus on the subset of participants whose choices can be plausibly rationalized within a EUT and CRRA theoretical framework, that is, they exclude from the estimation sample those "inconsistent" subjects who, after having chosen lottery B "switch back" to lottery A in a way that cannot be associated to any bounded interval of CRRA values[86].

Galizzi et al. (2016a) assume the random component ϵ_i to be independent from the observable characteristics x_i, identically and normally distributed, $\epsilon_i,| \ x_i \sim iid \ \mathrm{N}(0,\sigma^2)$, and they estimate β and σ via maximum likelihood (ML). The ML estimations account for the complex survey design by using appropriate sampling weights to draw valid inference for the adult population in the UK, and adjust standard errors at strata and PSU levels.

Here we use the individually estimated CRRA as the dependent variable in a set of linear regression models where the main explanatory variables are either the R2D:4D or the L2D:4D digit ratio measures, with and without a set of observable characteristics (i.e. sex, age, marital status, education, income (log), self-employed and employed status).

In order to replicate the analysis by Brañas-Garza et al. (2018) for the B-EG task in a representative sample of the UK population, here we also replicate their ordered probit (OP) estimations, where the dependent variable is directly the choice of the lottery in the B-EG task. In particular, the OP dependent variable takes value from 1 (lottery A, the safe lottery) to 6 (lottery F, the riskiest lottery), and thus increases with an individual's appetite for risk.

For the SOEP questions, the answers cannot be rationalized in a EUT and CRRA framework, and therefore here we simply use ordered probit (OP) estimations to model the choices in the 0-10 Likert scales. In particular, the dependent variable can take 11 values, associated with the 11 degrees of risk tolerance that the subject self-reported. These estimations thus directly replicate the analysis by Brañas-Garza et al. (2018) for the SOEP tasks in a representative sample of the UK population.

[86]The choices of some of the "inconsistent" subjects, in fact, can be easily managed by an interval regression model once we allow for behavioural "mistakes" in the sequence of choices. For example, if a subject switches to lottery B, then "switches back" to lottery A, and then switches to lottery B again and always chooses lottery B thereafter, his choices can be accommodated using a wide range of rra values whose lower bound coincides with the lower bound of the interval implied by the first switching point from lottery A to B, and the upper bound is given by the upper bound of the last switching point. See Galizzi et al. (2016a) for more on the "inconsistent" subjects.

4.2. Estimation of time discounting

We also look at the relationship between the digit ratio and time discounting (TD). Our estimations of time discounting are a direct adaptation of the risk aversion estimations by Galizzi et al. (2016a) to the case of time discounting. The same considerations discussed above for the estimation of risk aversion apply here with the obvious corresponding changes, for example in terms of the latent implicit discount rate (IDR) d_i, of the individual i, or of the upper bounds of the sets of implicit discount rates (d_{u1}, ..., d_{uJ}), rather than in terms of the relative risk aversion parameters.

Similarly to Galizzi et al. (2016a), we use standard interval regression models to estimate the latent relative implicit discount rate d_i, of the individual i, with d_i, a linear function of observable (x_i) and unobservable (ϵ_i) individual characteristics, i.e. $d_i = x_i'\beta + \epsilon_i$, and the observed choice y_i determined by:

$$y_i = \begin{cases} 1 & \text{si } x_i'\beta + \epsilon_i \leq d_{u1} \\ 2 & \text{si } d_{u1} \leq x_i'\beta + \epsilon_i \leq r_{u2} \\ . & ... \\ J & \text{si } r_{uJ-1} \leq x_i'\beta + \epsilon_i \end{cases}$$

where $1, 2, \ldots, J$ are the available choices in the experimental tasks (i.e. the switching points in each time preference task); andd_{u1}, d_{u2},...,d_{uJ}, are the upper bounds of the sets of implicit discount rate parameters consistent with the choices $1, 2, \ldots, J$.

Here we use the individually estimated IDR as the dependent variable in a set of linear regression models where the main explanatory variables are either the R2D:4D or the L2D:4D digit ratio measures, considered on their own or together with a set of observable characteristics (i.e. sex, age, marital status, education, income (log), employment status, interview charateristics).

5. Results

5.1. Descriptive summary statistics

A nationally representative sample of 661 individuals in the IP6 answered risk tolerance and time discounting questions in the behavioural economics module. Among those individuals, 551 also have measured their R2D:4D and 552 their L2D:4D in IP6. Further, 475 individuals have answered both R2D:4D and HL Low, 486 have answered both R2D:4D and HL High; 546 have answered both the R2D:4D and B-EG; 505 have answered both to the R2D:4D and SOEP-G and SOEP-F; and 504 have answered to the R2D:4D and the SOEP-H. Additionally, 551 individuals have answered to the R2D:4D and all FED and No-FED questions.

Similarly, 487 individuals have answered both the L2D:4D and HL High, 476 both the L2D:4D and HL Low; 547 have answered both the L2D:4D and B-EG; 507 have answered both the L2D:4D and SOEP-G; 506 have answered both to the L2D:4D and SOEP-F and SOEP-H. Additionally, 552 individuals have answered to the L2D:4D and all FED and No-FED questions.

Table 6 describes the main demographic and socio-economic characteristics of our sample.

Table 6: Description of the IP6 sample

	IP6 (n= 661)	
Dummy variables	Observation	Percentage
Female	362	54.77
Being single	456	53.96
Being an employee	299	45.23
Being self-employed	59	8.93
Having an A level of education	262	39.64
Being employed	643	95.92
Continuous variables	Mean	
Age	50.33	
Income (log)	7.19	

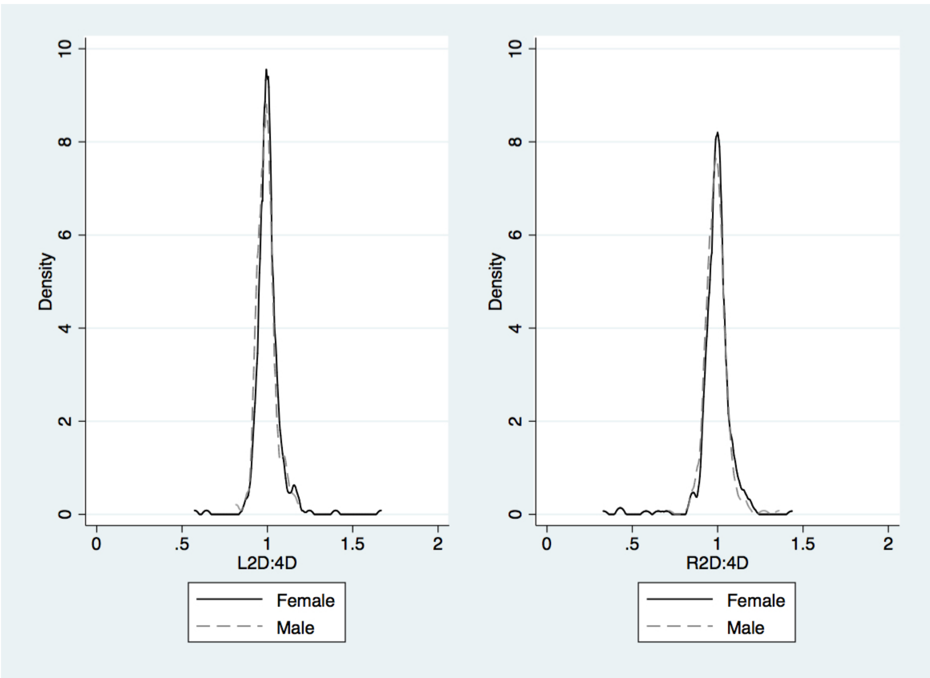
Note: the A level (stands for Advanced level) is a subject-based qualification conferred as part of the General Certificate of Education deliver by the Educational Government of United Kingdom to students completing secondary or pre-university education (usually aged 16-18 years old).

Obtaining such level is generally required for university entrance. See more on the following Government website: https://www.gov.uk/government/publications/get-the-facts-gcse-and-a-level-reform/get-the-facts-as-and-a-level-reform#what-new-as-and-a-levels-will-look-like.

5.1.1 digit ratios

Table 7 summarizes the L2D:4D and R2D:4D along each of the main individual characteristics. Overall, both the L2D:4D and R2D:4D of the male subjects are lower than those of female subjects. The average L2D:4D is 1.002 (SD= 0.080), and the average of R2D:4D is 0.992 (SD= 0.096). The average R2D:4D is 0.995 (SD = 0.115) for female subjects and 0.989 (SD= 0.055) for male subjects; the average L2D:4D is 1.010 (SD =0.109) for female subjects and 0.991 (SD=0.055) for male subjects. The difference of digit ratios between the two sexes is strongly statistically significant for the L2D:4D, but, interestingly not statistically significant for the R2D:4D. Figure 1(a) shows the sample distribution of the L2D:4D and of the R2D:4D for male and female subjects separately. We will go back to these findings on the links between digit ratios and sex in section 5.

Figure 1(a): Digit ratios for male and female subjects



Note: Kernel density for L2D: 4D for females (solid black line) and males (dashed gray line) in the left-hand side graph. Kernel density for R2D: 4D for female (solid black line) and male (dashed gray line) in the right-hand side graph.

Furthermore, individuals who are not self-employed have higher L2D:4D average (i.e. 1.004 with a SD = 0.004) than those who are self-employed (i.e. 0.973 with a SD = 0.078).

The same pattern occurs for the R2D:4D. The difference between self-employment is statistically significant for the L2D:4D, and not significant for the R2D:4D. Unemployed individuals are also more likely to have higher L2D:4D and R2D:4D average (i.e. 1.029 with a SD= 0.110 and 1.026 with a SD= 0.082, respectively) than those who are employed (i.e. 1.001 with a SD= 0.089 and 0.991 with a SD = 0.096). Other differences are not statistically significant.

Table 7: Summary statistics for digit ratios and control variables

	Left-hand (L2D:4D)			Right-hand (R2D:4D)		
	Mean	St.Dev	Diff.	Mean	St.Dev	Diff.
All	1.002	0.080		0.992	0.096	
Female	1.010	0.109	(+)***	0.995	0.115	(+)
Male	0.991	0.055		0.989	0.065	
Being self-employed	0.973	0.078	(-)**	0.982	0.114	(-)
Not being self-employed	1.004	0.004		0.993	0.094	
A level of education at most	1.001	0.109	(-)	0.993	0.007	(-)
Higher than A level	1.002	0.075		0.991	0.005	
Being employed	1.001	0.089	(-)	0.991	0.096	(-)*
Not being employed	1.029	0.110		1.026	0.082	
Obs.		552			551	

Note: significant differences between subsamples (two-tailed Wilcoxon rank-sum test) are shown in column (3) and (6). A (-) sign indicates a negative difference, a (+) sign indicates a positive differences. ***p<0.01, ** p<0.05, * p<0.1.

5.1.2 Risk tolerance

Table 8 summarizes the estimated risk aversion using both HL high and low. Female have higher risk aversion than male subjects when using the HL low measure (0.071 with a SD= 1.952), and lower when using the HL high measure (0.071 with a SD= 1.304) (i.e. -0.124 with a SD= 0.110 for HL low and 0.200 with a SD= 1.220 for HL high). The differences between sexes are positively significant for HL low, and negatively significant for HL high. The only other significant difference in risk preferences is for individuals who are self-employed, when risk aversion is based on the HL low measure. More precisely, individuals who are self-employed are significantly less risk averse (-0.358 with a SD= 1.875) than those who are not self-employed (0.016 with a SD= 1.885). Other individual characteristics do not show significant associations with risk aversion.

Table 8: Summary statistics for risk aversion (1/2)

	HL Low			HL High		
	Mean	St.Dev	Diff.	Mean	St.Dev	Diff.
All	-0.019	1.878		0.131	1.266	
Female	0.071	1.952	(+)*	0.071	1.304	(-)**
Male	-0.124	0.110		0.200	1.220	
Being self-employed	-0.358	1.875	(-)*	-0.052	1.294	(-)
Not being self-employed	0.016	1.885		0.150	1.263	
A level of education at most	-0.082	0.111	(-)	0.073	1.371	(-)
Higher than A level	0.021	0.108		0.128	1.095	
Being employed	-0.001	1.871	(+)	0.126	1.261	(-)
Not being employed	-0.442	2.040		0.260	1.395	
Obs.		569			586	

Note: significant differences between subsamples (two-tailed Wilcoxon rank-sum test) are shown in column (3) and (6). A (-) sign indicates a negative difference, a (+) sign indicates a positive differences. ***p<0.01, ** p<0.05, * p<0.1.

Table 9 summarizes the risk aversion based on the B-EG measure. We find that females are significantly more risk averse (i.e. 2.185 with a SD= 2.499) than males (i.e. 1.881 with a SD= 2.443). Other individual characteristics do not show significant associations with risk aversion.

Table 9: Summary statistics for risk aversion (2/2)

	B-EG		
	Mean	St.Dev	Diff.
All	2.948	2.477	
Female	2.185	2.499	(+)***
Male	1.881	2.443	
Being self-employed	1.795	2.636	(-)
Not being self-employed	2.074	2.461	
A level of education at most	1.830	2.471	(+)
Higher than A level	2.127	2.481	
Being employed	2.055	2.492	(+)
Not being employed	1.905	2.116	
Obs.		653	

Note: significant differences between subsamples (two-tailed Wilcoxon rank-sum test) are shown in column (3). A (-) sign indicates a negative difference, a (+) sign indicates a positive differences. ***p<0.01, ** p<0.05, * p<0.1.

Table 10 summarizes the risk attitude measures (i.e. SOEP-G, SOEP-F, and SOEP-H) along each of the main individual characteristics. It shows significant and positively difference in risk attitudes between the two sexes. Female are more likely to have higher risk aversion (i.e. 5.802 with a SD= 2.377 for SOEP-G, 7.052 with a SD= 2.216 for SOEP-F, and 6.988 with a SD= 2.424 for SOEP-H) than male (i.e. 5.084 with a SD= 2.433 for SOEP-G, 6.553 with a SD= 2.350 for SOEP-F, 6.692 with a SD= 2.274 for SOEP-H). Individuals who are self-employed have lower risk tolerance than those who are not self-employed only for SOEP-F (i.e. 6.200 with a SD= 2.067 versus 6.888 with a SD= 2.302). Those with an A level of education have lower risk tolerance (i.e. 5.208 with a SD= 2.397 for SOEP-G and 6.421 with a SD= 2.307 for SOEP-F) than those with not such education level (i.e. 5.653 with a SD= 2.435 for SOEP-G and 7.094 with a SD= 2.240 for SOEP-F). Other variables do not show significant differences.

Table 10: Summary statistics for risk attitudes

	Risk attitude					
	SOEP-G	Diff.	SOEP-F	Diff.	SOEP-H	Diff
All	5.476		6.825		6.854	
	(2.428)		(2.289)		(2.360)	
Female	5.802	(+)***	7.052	(+)***	6.988	(+)**
	(2.377)		(2.216)		(2.424)	
Male	5.084		6.553		6.692	
	(2.433)		(2.350)		(2.274)	
Being self-employed	5.527	(+)	6.200	(-)**	6.654	(-)
	(2.035)		(2.067)		(2.525)	
Not being self-employed	5.471		6.888		6.874	
	(2.465)		(2.302)		(2.344)	
A level of education at most	5.208	(-)**	6.421	(-)***	6.791	(-)
	(2.397)		(2.307)		(2.246)	
Higher than A level	5.653		7.094		6.895	
	(2.435)		(2.240)		(2.435)	
Being employed	5.491	(+)	6.847	(+)	6.882	(+)
	(2.425)		(2.253)		(2.353)	
Not being employed	5.120		6.320		6.200	
	(2.522)		(3.010)		(2.466)	
Obs.	603		602		602	

Note: significant differences between subsamples (two-tailed Wilcoxon rank-sum test) are shown in column (3) and (6). A (-) sign indicates a negative difference, a (+) sign indicates a positive differences. Standard deviations are in parenthesis. ***p<0.01, ** p<0.05, * p<0.1.

5.1.3 Time discounting

Tables 11 and 12 summarize the differences in implicit discount rates (IDR) along each of the main individual characteristics. For the first IRD questions we look at 1 month FED (FED 1 in column 1 of Table 11). Individuals who are employed have, on average, lower discount rate (i.e. 0.379 with a SD= 0.305) than those who are unemployed (i.e. 0.302 with a SD = 0.344); and individuals who are self-employed have, on average, higher discount rate (i.e. 0.491 with a SD= 0.367) than those who are not self-employed (i.e. 0.365 with a SD= 0.298). For the third set of IRD questions, we look at 12 month FED (FED 12 in column 5 of Table 11). In such questions, male have, on average higher discount rate (i.e. 0.388 with a SD= 0.302) than female (i.e. 0.433 with a SD= 0.304); and individual with an A level of education have, on average, lower discount rate (i.e. 0.390 with a SD= 0.316) than those with not such education level (i.e. 0.427 with a SD= 0.294). For the last IDR, we look at no-FED 12 months (no FED 12 in column 5 of Table 12), male have, on average, higher discount rate (i.e. 0.340 with a SD= 0.308) than females (i.e. 0.404 with a SD= 0.302); individuals with an A level of education have, on average, lower discount rate (i.e. 0.390 with a SD= 0.316) than those with not such education level (i.e. 0.394 with a SD= 0.302). IRD questions involving 3 months FED (FED 3 in column 3 of Table 11), 1 month no-FED (No-FED 1 in column 1 of Table 12), and 3 months no-FED (No-FED 3 in column 3 of Table 12) show no significant differences between all our variables.

Table 11: Summary statistics for implicit discount rates (1/2)

	FED 1	Diff.	FED 3	Diff.	FED 12	Diff.	Diff.	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(1) - (3)	(1) - (5)
All	0.376		0.359		0.412		(+)	(-)**
	(0.306)		(0.254)		(0.304)			
Female	0.368	(-)	0.354	(-)	0.433	(-)**		
	(0.299)		(0.243)		(0.304)			
Male	0.386		0.364		0.388			
	(0.350)		(0.266)		(0.302)			
Being self-employed	0.491	(+)**	0.386	(-)	0.448	(+)		
	(0.367)		(0.264)		(0.306)			
Not being self-employed	0.365		0.356		0.409			
	(0.298)		(0.253)		(0.303)			
Being employee	0.381	(+)	0.372	(+)	0.420	(+)		
	(0.305)		(0.251)		(0.308)			
Not being employee	0.372		0.348		0.406			
	(0.308)		(0.255)		(0.300)			
A level of education at most	0.392	(+)	0.364	(+)	0.390	(-)**		
	(0.324)		(0.263)		(0.316)			
Higher than A level	0.366		0.355		0.427			
	(0.294)		(0.248)		(0.294)			
Obs.				661				

Note: significant differences between subsamples (two-tailed Wilcoxon rank-sum test) are shown in column (2), (4) and (6). A (-) sign indicates a negative difference, a (+) sign indicates a positive differences. Standard deviations are in parenthesis. ***p<0.01, ** p<0.05, * p<0.1.

Table 12: Summary statistics for implicit discount rates (2/2)

	No-FED 1	Diff.	No-FED 3	Diff.	No-FED 12	Diff.	Diff.	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(1) - (3)	(1) - (5)
All	0.444		0.408		0.375		(+)***	(+)***
	(0.323)		(0.273)		(0.306)			
Female	0.429	(-)	0.408	Null	0.404	(+)***		
	(0.306)		(0.264)		(0.302)			
Male	0.461		0.408		0.340			
	(0.343)		(0.283)		(0.308)			
Being unemployed	0.372	(-)	0.379	(-)	0.412	(+)		
	(0.306)		(0.271)		(0.318)			
Being employed	0.447		0.409		0.374			
	(0.324)		(0.273)		(0.306)			
Being self-employed	0.508	(+)	0.426	(+)	0.383	(+)		
	(0.369)		(0.299)		(0.302)			
Not being self-employed	0.438		0.406		0.374			
	(0.318)		(0.270)		(0.307)			
A level of education at most	0.458	(+)	0.405	(-)	0.346	(-)***		
	(0.352)		(0.280)		(0.311)			
Higher than A level	0.434		0.410		0.394			
	(0.304)		(0.268)		(0.302)			
Obs.				661				

Note: significant differences between subsamples (two-tailed Wilcoxon rank-sum test) are shown in column (2), (4) and (6). A (-) sign indicates a negative difference, a (+) sign indicates a positive differences. Standard deviations are in parenthesis. ***$p<0.01$, ** $p<0.05$, * $p<0.1$

5.2. Correlation analysis

Table 13 report pairwise correlations among the main variables of interest . We first note, that L2D:4D and R2D:4D are positively correlated (0.573, p=0.000). Next, looking at the measures of risk taking, we find a significant positive correlation between the HL Low and HL High measures of risk aversion (0.816, p = 0.0000). We note that HL High and HL Low measures of risk aversion are weakly correlated with the self-reported measures of risk attitudes. This is in line with other evidence of moderate correlations between the two methods (Filippin and Crosetto (2016); Galizzi et al. (2016a)). This may indicate that self-reported RA and RP revealed through experimental tasks with real monetary incentives capture different aspects of individual risk taking. Further, only the HL Low measure of risk aversion is weakly but positively associated with two measures of time discounting.

Furthermore, the correlation analysis reveals an interesting pattern of associations between digit ratios and our measures of risk tolerance. There is a negative and marginally significant correlation between R2D:4D and HL Low. So, the higher is the R2D:4D – that is, the lower the prenatal testosterone exposure – the less likely are the subjects to take risk in the HL Low incentivized experiments. There are negative and significant correlations between R2D:4D and all the three self-reported measure of risk tolerance. The corresponding associations with L2D:4D are also negative and statistically significant but only for the financial and health risk attitudes. Interestingly, however, there are no other significant correlations between digit ratios and any of the other risk tolerance or time discounting measures.

For time discounting, there are no significant associations between both the digit ratios and the risk tolerance measures. The only exceptions are FED 12 and no-FED 12 questions that are both positively and significantly correlated with HL Low.

Table 13: Pairwise correlations between the main variables

	R2D:4D	L2D:4D	HL Low	HL High	B-EG	SOEP-G	SOEP-F	SOEP-H	FED 1	FED 3	FED 12	No-FED 1	No-FED 3	No-FED 12
R2D:4D	1.000													
L2D: 4D	0.473***	1.000												
	(0.000)													
HL Low	-0.088*	-0.035	1.000											
	(0.055)	(0.441)												
HL High	-0.028	0.027	0.816***	1.000										
	(0.534)	(0.555)	(0.000)											
B-EG -	0.018	0.007	0.127***	0.164***	1.000									
	(0.668)	(0.875)	(0.002)	(0.000)										
SOEP-G	-0.109**	-0.056	0.098**	0.150***	0.103**	1.000								
	(0.013)	(0.206)	(0.025)	(0.000)	(0.011)									
SOEP-F	-0.095**	-0.083*	0.102**	0.138***	0.161***	0.604***	1.000							
	(0.033)	(0.062)	(0.020)	(0.001)	(0.000)	(0.000)								
SOEP-H	-0.128***	-0.108**	0.039	0.057	0.096**	0.553***	0.570***	1.000						
	(0.004)	(0.015)	(0.276)	(0.185)	(0.019)	(0.000)	(0.000)							
FED 1	-0.016	-0.023	0.063	0.054	0.026	0.038	-0.030	-0.034	1.000					
	(0.704)	(0.590)	(0.129)	(0.555)	(0.553)	(0.351)	(0.459)	(0.402)						
FED 3	-0.015	-0.048	0.051	0.022	0.057	-0.023	0.033	-0.027	0.523***	1.000				
	(0.716)	(0.248)	(0.185)	(0.494)	(0.143)	(0.033)	(0.375)	(0.503)	(0.000)					
FED 12	-0.013	-0.063	0.071**	0.029	0.050	0.042	0.024	-0.035	-0.036	0.283***	1.000			
	(0.774)	(0.134)	(0.090)	(0.481)	(0.237)	(0.652)	(0.632)	(0.375)	(0.374)	(0.000)				
No-FED 1	0.006	-0.036	-0.007	0.039	0.050	0.042	0.024	-0.035	0.527***	0.473***	0.203***	1.000		
	(0.871)	(0.394)	(0.859)	(0.345)	(0.201)	(0.304)	(0.559)	(0.385)	(0.000)	(0.000)	(0.000)			
No-FED 3	-0.056	-0.017	-0.016	-0.030	-0.005	0.031	0.010	0.006	0.391***	0.529***	0.412***	0.442***	1.000	
	(0.188)	(0.696)	(0.684)	(0.462)	(0.893)	(0.449)	(0.810)	(0.878)	(0.000)	(0.000)	(0.000)	(0.000)		
No-FED 12	-0.017	-0.025	0.074**	0.013	0.027	0.034	0.039	-0.014	0.211***	0.295***	0.568***	0.192***	0.420***	1.000
	(0.692)	(0.560)	(0.077)	(0.124)	(0.746)	(0.410)	(0.335)	(0.723)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Note: *** p<0.01, ** p<0.05, * p<0.1.

5.3. Regression analysis

5.3.1 digit ratio and risk tolerance

We conduct regression analysis to explore the link between digit ratio and risk tolerance, with and without controlling for observable characteristics (i.e. sex, age, marital status, education, income (log), self-employed and employed status).

Risk attitudes We first consider the relationship between digit ratio and risk attitudes. The OP regression models use IP6 and R2D:4D (Table 14) and then replicate with the L2D:4D (Tables 15).

We find that the R2D:4D is negatively and marginally significantly associated with SOEP-G (with and without control variables), but not with the SOEP-F or SOEP-H. The L2D:4D is not significantly associated with any measures of risk attitudes.

Table 14: Risk attitude, right digit ratios and individual characteristics

	SOEP-G	SOEP-G	SOEP-F	SOEP-F	SOEP-H	SOEP-H
R2D:4D	-1.102*	-1.184**	-0.663	-0.728	-1.185	-1.204*
	(0.572)	(0.564)	(0.575)	(0.567)	(0.716)	(0.703)
Control variables	No	Yes	No	Yes	No	Yes
Observations	529	527	529	527	528	526
Positive weights	436	434	436	434	435	433

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

Table 15: Risk attitude, left digit ratios and individual characteristics

	SOEP-G	SOEP-G	SOEP-F	SOEP-F	SOEP-H	SOEP-H
L2D:4D	-0.165	-0.586	0.128	-0.349	0.008	-0.285
	(0.516)	(0.518)	(0.697)	(0.683)	(0.717)	(0.718)
Control variables	No	Yes	No	Yes	No	Yes
Observations	532	530	531	529	531	529
Positive weights	439	437	438	436	438	436

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

Risk aversion We then move to risk aversion. We first replicate the estimates by Brañas-Garza et al. (2018) where the dependent variable of the ordered probit (OP) estimations is directly the choice of the lottery in the B-EG task. As it can be seen from Tables 16 and 17, the OP regressions show no statistically significant associations between the digit ratios and the choice of the risky lottery in the B-EG experimental task. Therefore in our representative sample of the UK population we do not replicate the findings by Brañas-Garza et al. (2018) using a convenience sample of students in London.

Table 16: Ordered probit for choice of lottery in the B-EG task (R2D: 4D)

	B-EG	B-EG	B-EG	B-EG	B-EG
R2D:4D	0.280	0.251	-1.204	0.293	0.267
	(0.568)	(0.573)	(1.335)	(0.588)	(0.594)
Female		0.246*	-1.779		0.236*
		(0.129)	(1.574)		(0.130)
R2D:4D x Female			2.043		
			(1.601)		
Control variables	No	No	No	Yes	Yes
Observations	567	567	567	565	565
Positive weights	474	474	474	472	472

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

Table 17: Ordered probit for choice of lottery in the B-EG task (L2D: 4D)

	B-EG	B-EG	B-EG	B-EG	B-EG
L2D:4D	0.763	0.544	2.548	0.694	0.495
	(0.813)	(0.803)	(1.537)	(0.819)	(0.809)
Female		0.260**	3.023*		0.255*
		(0.128)	(1.773)		(0.128)
L2D:4D x Female			-2.782		
			(1.767)		
Observations	569	569	569	567	567
Positive weights	476	476	476	474	474
Control variables	No	No	No	Yes	Yes
Observations	567	567	567	565	565
Positive weights	474	474	474	472	472

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

We next use the individually estimated CRRA as the dependent variable in a set of linear regression models where the main explanatory variables are either the R2D:4D or the L2D:4D digit ratio measures, with and without a set of observable characteristics. The regression models use IP6 and the R2D:4D (Table 18), and then replicate with the L2D: 4D (Table 19). Also these other regressions show no statistically significant associations between the digit ratios and different measures of individual risk aversion.

Table 18: Risk aversion, right digit ratios and individual characteristics

	HL Low	HL Low	HL High	HL High	B-EG	B-EG
R2D:4D	-1.553	-1.595	-0.344	-0.377	0.972	0.912
	(1.350)	(1.327)	(0.894)	(0.868)	(1.270)	(1.322)
Control variables	No	Yes	No	Yes	No	Yes
Observations	503	503	513	513	565	565
Positive weights	411	411	420	420	472	472
R-squared	0.006	0.018	0.001	0.020	0.001	0.029

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

Table 19: Risk aversion, left digit ratios and individual characteristics

	HL Low	HL Low	HL High	HL High	B-EG	B-EG
L2D:4D	0.993	0.927	1.467	1.625	1.590	0.889
	(1.292)	(1.254)	(1.097)	(1.113)	(1.769)	(1.730)
Control variables	No	Yes	No	Yes	No	Yes
Observations	505	505	515	515	567	567
Positive weights	413	413	422	422	474	474
R-squared	0.002	0.014	0.006	0.030	0.002	0.033

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

5.3.2 digit ratio and time discounting

We next turn to the relationship between the digit ratio and time discounting (TD). We use the individually estimated IDR as the dependent variable in a set of linear regression models where the main explanatory variables are either the R2D:4D or the L2D:4D digit ratio measures, considered on their own or together with a set of observable characteristics. Tables are organized in the same way as for risk tolerance. In particular, the OLS regression models use IP6 and the R2D: 4D (Tables 20 and 21) and then replicate with the L2D: 4D

(Tables 22 and 23). We first look at the R2D: 4D (or L2D: 4D) as the only explanatory variable for TD, and then add the control variables.

As it can be seen, we find no statically significant association between the IDR measures and both the right-hand and the left-hand digit ratios.

Table 20: Implicit discount rates, right digit ratios and individual characteristics (1/3)

	FED 1	FED 1	FED 3	FED 3	FED 12	FED 12
R2D:4D	0.002	0.020	-0.002	-0.006	0.045	0.026
	(0.118)	(0.119)	(0.010)	(0.099)	(0.162)	(0.170)
Control variables	No	Yes	No	Yes	No	Yes
Observations	570	568	570	568	570	568
Positive weights	477	475	477	475	477	475
R-squared	0.000	0.026	0.000	0.017	0.000	0.037

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

Table 21: Implicit discount rates, right digit ratios and individual characteristics (2/2)

	No-FED 1	No-FED 1	No-FED 3	No-FED 3	No-FED 12	No-FED 12
R2D:4D	0.194	0.214	-0.091	-0.098	0.054	0.038
	(0.127)	(0.138)	(0.159)	(0.163)	(0.156)	(0.168)
Control variables	No	Yes	No	Yes	No	Yes
Observations	570	568	570	568	570	568
Positive weights	477	475	477	574	477	475
R-squared	0.003	0.028	0.001	0.017	0.000	0.031

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

Table 22: Implicit discount rates, left digit ratios and individual characteristics (1/2)

	FED 1	FED 1	FED 3	FED 3	FED 12	FED 12
L2D:4D	-0.031	0.033	-0.134	-0.146	-0.159	-0.152
	(0.146)	(0.151)	(0.146)	(0.149)	(0.203)	(0.209)
Control variables	No	Yes	No	Yes	No	Yes
Observations	572	570	572	570	572	570
Positive weights	479	477	479	477	479	477
R-squared	0.000	0.025	0.001	0.015	0.001	0.036

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

Table 23: Implicit discount rates, left digit ratios and individual characteristics (2/2)

	No-FED 1	No-FED 1	No-FED 3	No-FED 3	No-FED 12	No-FED 12
L2D:4D	-0.004	0.029	0.099	0.103	0.034	0.017
	(0.192)	(0.197)	(0.150)	(0.147)	(0.175)	(0.179)
Control variables	No	Yes	No	Yes	No	Yes
Observations	572	57	0 572	570	572	570
Positive weights	479	477	479	477	479	477
R-squared	0.000	0.026	0.001	0.017	0.000	0.031

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

Further, in Tables 24 and 25 we also look at the associations between both the right-hand and left-hand digit ratios and immediacy effect and hyperbolic discounting. The immediacy effect signals a "present bias" towards any outcome occurring now versus in the future, and here is operationally proxied by the ratio of the 1 month No FED/1 month FED estimated implicit discount rate (IE1)[87].

[87] We provide in the Appendix Section two other immediacy effects: ratio of no FED/FED 3 months estimated implicit discount rate (IE3); and the ratio of no FED/FED 12 months estimated implicit discount rate (IE12). These further robustness checks confirm no statistically significant associations between digit ratios and immediacy effects.

Hyperbolic discounting signals implicit discount rates which decline over increasing time horizons, and here is operationally proxied by either the ratio of the 1 month no-FED/12 months no-FED estimated implicit discount rate (HD12) or by the ratio of the 1 month no-FED/3 months no-FED estimated implicit discount rate (HD3).

Results show no significant associations between immediacy effect or hyperbolic discounting and both digit-ratios. The only exception is a marginally significant association between the HD12 and the left-hand digit ratio.

Table 24: Immediacy effect and digit ratios

	IE1	IE1	IE1	IE1
R2D:4D	1.302	1.271		
	(1.224)	(1.312)		
L2D:4D			-0.007	-0.667
			(1.848)	(2.056)
Control variables	No	Yes	No	Yes
Observations	570	568	572	570
Positive weights	477	475	479	477
R-squared	0.001	0.017	0.000	0.016

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

Table 25: Hyperbolic discounting and digit ratios

	HD12	HD12	HD12	HD12	HD3	HD3	HD3	HD3
R2D:4D	-2.794	-2.551			-0.519	-0.355		
	(2.088)	(2.240)			(1.073)	(0.874)		
L2D:4D			-4.725*	-4.922**			-0.930	-0.652
			(2.562)	(2.427)			(1.382)	(0.855)
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Observations	570	568	572	570	570	568	572	570
Positive weights	477	475 4	79	477	477	475	579	477
R-squared	0.002	0.028	0.005	0.034	0.000	0.019	0.000	0.019

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

6. Gender differences in risk tolerance and time preferences can be explained by the digit ratio

6.1. Descriptive summary statistics divided by sex

6.1.1 Digit ratio

Table 26 summarizes our L2D:4D and R2D:4D, risk tolerance and time discounting measures by sex. Overall, both the L2D:4D and R2D:4D of the male subjects are lower than those of female subjects. The average R2D:4D is 0.995 (SD = 0.115) for female subjects and 0.989 (SD= 0.055) for male subjects; the average L2D:4D is 1.010 (SD =0.109) for female subjects and 0.991 (SD=0.055) for male subjects. The difference between sexes is statistically significant for the L2D:4D, but not significant for the R2D:4D.

Table 26: Hyperbolic discounting and digit ratios

	Digit Ratio			
	Female	Male	Diff.	Obs.
	(1)	(2)	(3)	(4)
R2D:4D	0.995	0.989	(+)	551
	(0.115)	(0.065)		
L2D:4D	1.010	0.991	(+)***	552
	(0.109)	(0.055)		

Note: significant differences between subsamples (two-tailed Wilcoxon rank-sum test) are shown in column (3). A (-) sign indicates a negative difference, a (+) sign indicates a positive differences. Standard deviations are in parenthesis. ***p<0.01, ** p<0.05, * p<0.1.

6.1.2 Risk tolerance

Overall, female have lower risk-tolerance when using risk attitude measures. The average general risk attitude is 5.802 (SD = 2.377), the average health risk attitude is 6.987 (SD = 2.424), and the average financial risk attitude is 7.051 (SD= 2.216) for female subjects. Regarding with male subjects, the values are 5.084 (SD= 2.436), 6.692 (SD= 2.274), and 6.553 (SD= 2.350) respectively. All differences are significant (see more on Table 27).

However, the evidence is mixed regarding risk aversion. For women, the average CRRA based on the HL low measure is 0.071(SD= 1.952), the average of HL high risk preference is 0.072 (SD= 1.304) for female subjects; the average of HL low risk preference is -0.124 (SD= 1.786), the average of HL high-risk preference is 0.200 (SD= 1.220) for male subjects. The average of B-EG is 2.186 (SD=2.499) for female subjects, and 1.881 (SD=2.443) for male subjects. Figure 1(b) shows the histogram of risk preferences and Figure 1(c) shows the histogram of risk attitudes for male and female subjects.

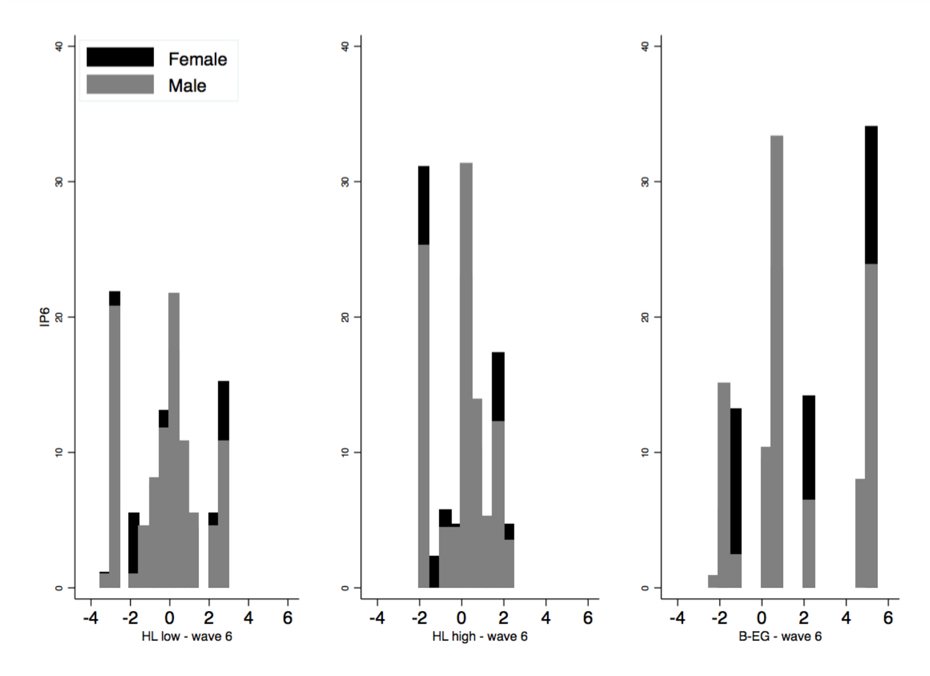
Controlling for sex allows capturing for some variations in risk tolerance that could be due to behavioral or cultural factors that influence risk acceptance. The 2D:4D coefficient captures whether being exposed to testosterone during pregnancy shape risk tolerance. The interaction of these two variables captures the within-gender variation in testosterone exposure. Even though male (female, respectively) received more (less, respectively) testosterone *in-utero* than female (male, respectively), some male (female, respectively) could have received more of it than others. This interaction term is never significantly associated with risk tolerance: heterogeneous exposure to pre-natal testosterone has no impact on current level of risk acceptance.

Table 27: Summary statistics for risk attitudes and risk aversion for male and female subjects

	Risk tolerance			
	Females	Males	Diff.	Obs.
	(1)	(2)	(3)	(4)
HL Low	0.071	-0.124	(+)*	569
	(1.952)	(1.786)		
HL High	0.072	0.200	(-)**	586
	(1.304)	(1.220)		
B-EG	2.186	1.881	(-)***	653
	(2.499)	(2.443)		
SOEP-G	5.802	5.084	(+)***	603
	(2.377)	(2.436)		
SOEP-H	6.987	6.692	(+)**	602
	(2.424)	(2.274)		
SOEP-F	7.051	6.553	(+)***	602
	(2.216)	(2.350)		

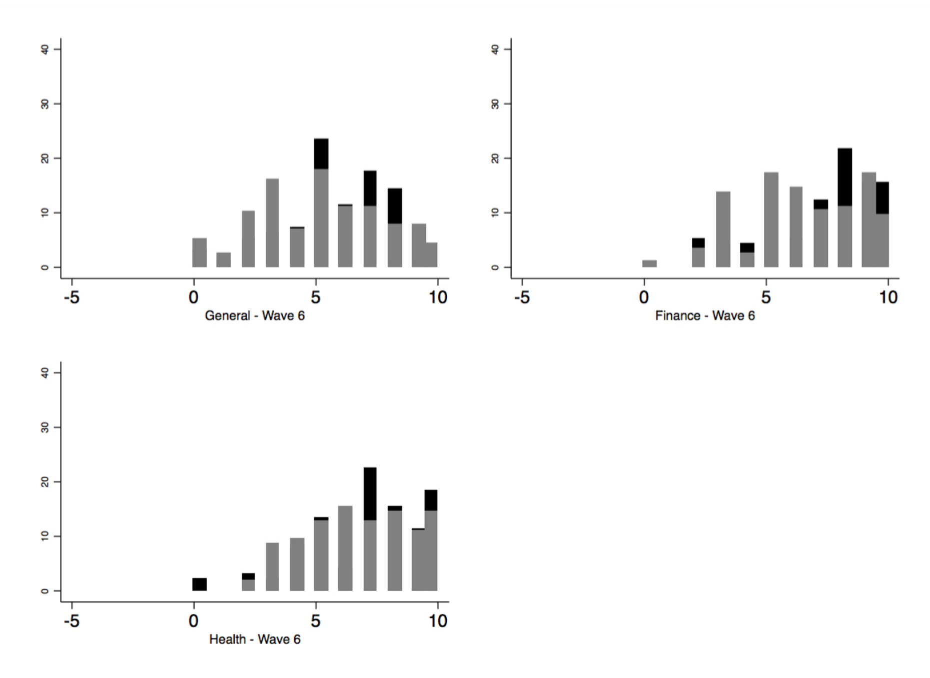
Note: significant differences between subsamples (two-tailed Wilcoxon rank-sum test) are shown in column (3). A (-) sign indicates a negative difference, a (+) sign indicates a positive differences. Standard deviations are in parenthesis. ***p<0.01, ** p<0.05, * p<0.1.

Table 1(b): Distribution of risk aversion for male and female subjects



Note: Histogram of risk preferences for female (black), and male (black) subjects.

Table 1(c): Distribution of risk attitudes for male and female subjects



Note: Histogram for risk attitude for female (black) and male (gray) subjects.

6.1.3 Time discounting

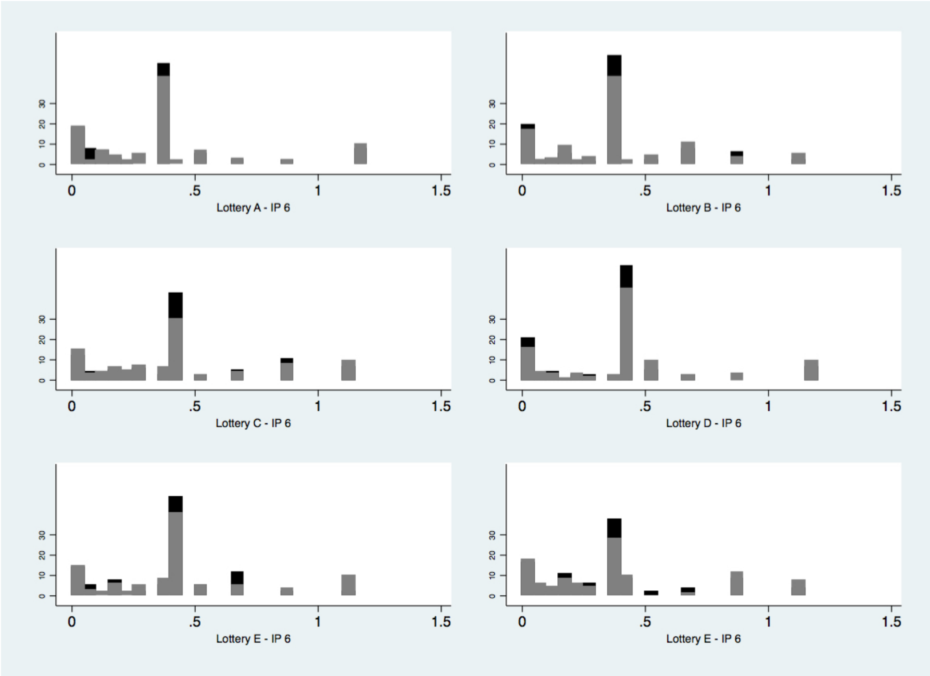
Female and male subjects do not significantly differ in their implicit discount rates, as reported in the following Table. They differ only for FED 12 and no-FED 12 questions, where women discount one-year periods more heavily than men (i.e. 0.432 with a SD= 0.304 for FED 12 questions, and 0.404 with a SD= 0.303 for no-FED 12 questions for women compared to 0.388 with a SD= 0.302 for FED 12 questions, and 0.340 with a SD= 0.308 for no-FED 12 questions for men). Figure 1(d) shows the histogram of time preferences for male and female subjects.

Table 28: Summary statistics for implicit discount rates for male and female subjects

	Time discounting			
	Females	Males	Diff.	Obs.
	(1)	(2)	(3)	(4)
FED 1	0.368	0.386	(-)	661
	(0.299)	(0.315)		
FED 3	0.354	0.364	(-)	661
	(0.243)	(0.265)		
FED 12	0.432	0.388	(+)**	661
	(0.304)	(0.302)		
No-FED 1	0.429	0.461	(+)	661
	(0.306)	(0.343)		
No-FED 3	0.408	0.408	Null	661
	(0.264)	(0.283)		
No-FED 12	0.404	0.340	(+)***	661
	(0.303)	(0.308)		

Note: significant differences between subsamples (two-tailed Wilcoxon rank-sum test) are shown in column (3). A (-) sign indicates a negative difference, a (+) sign indicates a positive differences. Standard deviations are in parenthesis. ***p<0.01, ** p<0.05, * p<0.1.

Table 1(d): distribution of implicit discount rates for male and female subjects (FED 1, FED 3, FED 12; no-FED 1, no-FED 2, no-FED 12)



Note: Histogram for risk attitude for female (black) and male (gray) subjects.

6.2. Correlation analysis divided by sex

Table 29 reports pairwise correlations among the main variables of interest . We first note, that being a woman in our representative sample is positively and significantly correlated with both the SOEP-G (i.e. 0.147, p= 0.000) and SOEP-F (i.e. 0.108, p= 0.000), but not with the SOEP-H. There is not statistically significant association between sex and risk aversion as measured by the experimental tasks. Next, being a woman is also not significantly correlated with time discounting. The only exception is the time discounting for the one-year period with no FED, which is positively and significantly correlated with being a woman (0.104, p=0.007).

Table 29: Correlation between sex and risk tolerance measures

	R2D:4D	L2D:4D	HL Low	HL High	B-EG	SOEP-G	SOEP-F	SOEP-H	FED 1	FED 3	FED 12	No-FED 1	No-FED 3	No-FED 12
Female	0.030	0.100**	0.052	-0.050	0.061	0.147***	0.108***	0.062	-0.030	-0.020	0.073*	-0.049	0.001	0.104***
	(0.486)	(0.017)	(0.216)	(0.223)	(0.118)	(0.000)	(0.008)	(0.126)	(0.444)	(0.600)	(0.058)	(0.205)	(0.990)	(0.007)

Note: *** p<0.01, ** p<0.05, * p<0.1.

6.3. Regression analysis results

6.3.1 Sex and risk attitude

We conduct further regression analysis to explore the link between digit ratio and risk taking, controlling for observable characteristics (i.e. sex, age, marital status, education, income (log), employment and self-employment status). We first look at risk attitudes. To do so we use an OP. The regression models start with R2D:4D (Table 30), and then replicate the analysis with L2D:4D (Table 31). We first look at the R2D:4D (or L2D:4D) and sex as the only explanatory variables, and then add the interaction terms between these variables.

We find that the interaction terms between sex and both right and left-hand digit ratios are never significantly associated with the measure of risk attitudes.

Table 30: Relationship between sex, right-hand digit ratio and risk attitudes

	SOEP-G	SOEP-G	SOEP-F	SOEP-F	SOEP-H	SOEP-H
Female x R2D:4D		0.514		1.298		-0.983
		(1.385)		(1.475)		(1.486)
R2D:4D	-1.184**	-1.550	-0.728	-1.658	-1.204*	-0.511
	(0.564)	(1.279)	(0.567)	(1.294)	(0.703)	(1.197)
Female	0.336***	-0.174	0.254**	-1.035	0.168	1.144
	(0.106)	(1.383)	(0.106)	(1.481)	(0.110)	(1.483)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	527	527	527	527	526	526
Positive weights	434	434	434	434	433	433

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

Table 31: Relationship between sex, left-hand digit ratio and risk attitudes

	SOEP-G	SOEP-G	SOEP-F	SOEP-F	SOEP-H	SOEP-H
Female x L2D:4D		-0.0761		-1.535		-2.134
		(1.225)		(1.536)		(1.417)
L2D:4D	-0.586	-0.531	-0.349	0.762	-0.285	1.261
	(0.518)	(1.141)	(0.683)	(1.411)	(0.718)	(1.335)
Female	0.353***	0.429	0.260**	1.784	0.165	2.283
	(0.104)	(1.215)	(0.104)	(1.525)	(0.113)	(1.408)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	530	530	529	529	529	529
Positive weights	437	437	436	436	436	436

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

6.3.2 Sex and risk aversion

We next consider the relationships between digit ratio and risk aversion. We investigate such relationship using linear regression models. All these models are conducting using a first sex with R2D:4D (see more in Table 32) or sex with L2D:4D (see more in Table 33) as two explanatory variables. We then add the interactions between those two variables.

We find no systematic pattern of association between risk aversion and interaction terms. The interaction term between sex and R2D:4D is positively and marginally significantly associated only with the risk aversion measured by the HL High task. The interaction term between sex and L2D:4D, on the other hand, is negatively and marginally significantly associated only with the risk aversion measured by the B-EG task.

Table 32: Relationship between sex, right-hand digit ratio and risk aversion

	HL Low	HL Low	HL High	HL High	B-EG	B-EG
Female x R2D:4D		2.776		2.447*		4.358
		(2.135)		(1.329)		(3.390)
R2D:4D	-1.595	-3.566**	-0.377 -	2.028*	0.912	-2.193
	(1.327)	(1.689)	(0.868)	(1.146)	(1.322)	(2.782)
Female	0.098	-2.655	-0.138	-2.563*	0.654**	-3.669
	(0.173)	(2.114)	(0.125)	(1.306)	(0.304)	(3.369)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	503	503	513	513	565	565
Positive weights	411	411	420	420	472	472
R-squared	0.018	0.022	0.020	0.026	0.029	0.034

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

Table 33: Relationship between sex, left-hand digit ratio and risk aversion

	HL Low	HL Low	HL High	HL High	B-EG	B-EG
Female x L2D:4D		-3.088		-1.084		-6.160*
		(2.439)		(1.909)		(3.671)
L2D:4D	0.927	3.171	1.625	2.331	0.889	5.330
	(1.254)	(2.483)	(1.113)	(1.718)	(1.730)	(3.244)
Female	0.076	3.139	-0.170	0.908	0.701**	6.818*
	(0.164)	(2.447)	(0.124)	(1.898)	(0.299)	(3.706)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	505	505	515	515	567	567
Positive weights	413	413	422	422	474	474
R-squared	0.014	0.018	0.030	0.030	0.033	0.039

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

6.3.3 Sex and time discounting

We now turn to the relationship between the digit ratio, time discounting, and sex. Tables are organized in the same manner as for the RA and RP. The OLS regression models start with R2D:4D (Tables 34 and 35) and then replicate for L2D:4D (Tables 26 and 37). We find that the interaction between sex and the right-hand digit ratio, and the interaction between sex and the left-hand digit ratio, are not significantly associated with any estimated measure of the implicit discount rates.

Controlling for sex allows capturing some of the variations in risk tolerance that could be due to behavioral or cultural factors that influence risk acceptance. The 2D:4D coefficient captures whether being exposed to testosterone during pregnancy shapes risk tolerance. The interaction of these two variables captures the within-gender variation in testosterone exposure. Even though male (female, respectively) received more (less, respectively) testosterone *in-utero* than female (male, respectively), some male (female, respectively) could have received more of it than others. This interaction term is never significantly associated with risk tolerance: heterogeneous exposure to pre-natal testosterone has no impact on current level of risk acceptance.

Table 34: Relationship between sex, right-hand digit ratio and implicit discount rates (1/2)

	FED 1	FED 1	FED 3	FED 3	FED 12	FED 12
Female x R2D:4D		0.404		0.385		0.218
		(0.357)		(0.248)		(0.423)
R2D:4D	0.020	-0.268	-0.0058	-0.280	0.026	-0.129
	(0.119)	(0.329)	(0.0990)	(0.232)	(0.170)	(0.397)
Female	0.018	-0.382	0.024	-0.357	0.049 -0.167	
	(0.026)	(0.352)	(0.024)	(0.250)	(0.032)	(0.421)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	568	568	568	568	568	568
Positive weights	411	411	420	420	472	472
R-squared	0.026	0.029	0.017	0.020	0.037	0.038

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

Table 35: Relationship between female, right-hand digit ratio and implicit discount rates (2/2)

	No-FED 1	No-FED 1	No-FED 3	No-FED 3	No-FED 12	No-FED 12
Female x R2D:4D		0.153		-0.171		-0.288
		(0.417)		(0.327)		(0.422)
R2D:4D	0.214	0.104	-0.0983	0.0235	0.0377	0.243
	(0.138)	(0.339)	(0.163)	(0.292)	(0.168)	(0.390)
Female	-0.004	-0.156	0.018	0.187	0.0539*	0.340
	(0.023)	(0.408)	(0.030)	(0.320)	(0.029)	(0.420)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	568	568	568	568	568	568
Positive weights	475	475	475	475	475	475
R-squared	0.028	0.028	0.017	0.018	0.031	0.032

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

Table 36: Relationship between gender, left-hand digit ratio and implicit discount rates (1/2)

	FED 1	FED 1	FED 3	FED 3	FED 12	FED 12
L2D:4D x Female	-0.002	0.128	0.643			
	(0.414)	(0.388)	(0.456)			
L2D:4D	0.033	0.033	-0.146	-0.238	-0.152	-0.615
	(0.151)	(0.386)	(0.149)	(0.350)	(0.209)	(0.403)
Female	0.015	0.015	0.022	-0.105	0.047	-0.591
	(0.025)	(0.413)	(0.025)	(0.389)	(0.033)	(0.460)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	570	570	570	570	570	570
Positive weights	477	477	477	477	477	477
R-squared	0.025	0.025	0.015	0.015	0.036	0.040

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

Table 37: Relationship between sex, left-hand digit ratio and implicit discount rates (2/2)

	No-FED 1	No-FED 1	No-FED 3	No-FED 3	No-FED 12	No-FED 12
L2D:4D x Female	-0.274	-0.0825	-0.164			
	(0.489)	(0.379)	(0.422)			
L2D:4D	0.029	0.227	0.103	0.162	0.017	0.135
	(0.197)	(0.457)	(0.147)	(0.350)	(0.179)	(0.385)
Female	-0.004	0.269	0.0134	0.095	0.054*	0.217
	(0.023)	(0.484)	(0.029)	(0.375)	(0.023)	(0.427)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	570	570	570	570	570	570
Positive weights	477	477	477	477	477	477
R-squared	0.026	0.027	0.017	0.017	0.031	0.031

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

Further, we also look at the associations with the immediacy effect (IE 1 in Table 38[88]), and with hyperbolic discounting (HD 1 and HD 2 in Table 39). We do not find any association between immediacy effect or hyperbolic discounting, digit ratios and sex. The only exception is a statistically significant and negative association between the 1/12 months no-FED questions, and the left-digit ratio.

Table 38: Relationship between immediacy effect, digit ratios, and sex

	IE 1	IE 1	IE 1	IE 1
R2D:4D x Female		-0.697		
		(3.666)		
R2D :4D	1.271	1.767		
	(1.312)	(3.519)		
Female	-0.192	0.499	-0.173	2.564
	(0.440)	(3.447)	(0.456)	(4.681)
L2D:4D			-0.667	1.319
			(2.056)	(3.854)
L2D:4D x Female				-2.756
				(4.686)
Control variables	No	Yes	No	Yes
Observations	568	568	570	570
Positive weighs	475	475	477	477
R-squared	0.017	0.017	0.016	0.017

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

[88] In the Appendix Section, which provides such association for IE 3 and IE 12.

Table 39: Relationship between hyperbolic discounting, digit ratio, and female

	HD 12	HD 12	HD 12	HD 12	HD 3	HD 3	HD 3	HD 3
R2D:4D x Female		2.069			0.514			
		(4.458)			(2.149)			
R2D:4D	-2.551	-4.024		-0.355	-0.722			
	(2.240)	(2.850)		(0.874)	(1.663)			
Female	-0.546	-2.598	-0.497	-3.284	-0.0605	-0.571	-0.0423	1.075
	(0.411)	(4.507)	(0.408)	(5.142)	(0.367)	(2.328)	(0.368)	(3.217)
L2D:4D		-4.922**	-6.944**		-0.652	0.159		
		(2.427)	(3.361)		(0.855)	(2.520)		
L2D:4D x Female			2.807				-1.125	
			(5.056)			(3.156)		
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Positive weights	475	475	477	477	475	475	477	477
Observations	568	568	570	570	568	568	570	570
R-squared	0.028	0.028	0.034	0.034	0.019	0.019	0.019	0.019

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include sex, level of education, age, marital status, employment and self-employment status, and income.

7. Discussion and conclusion

To our knowledge, ours is the first study to date to systematically report, for a representative sample of the UK population, the associations between digit ratios and risk tolerance and time discounting.

We have four main findings. First, the R2D:4D is negatively and marginally significantly associated with the SOEP-G measure of risk attitudes. Subjects with lower R2D:4D tend to self-report lower willingness to take risks in general and in health. This result is only marginally different from the findings by Brañas-Garza et al. (2018) who found no significant association at all between the digit ratios and the same self-reported risk attitudes questions in a large sample of students.

Second, in contrast to our findings on risk attitudes, neither the R2D:4D nor the L2D:4D are significantly associated with risk aversion as measured and estimated by incentive-compatible experimental tests. This lack of significant association between digit ratios and incentive-compatible measures of risk aversion is robust across different experimental tasks and across different estimations of risk aversion conducted either directly in terms of the choice among the risky lotteries, or in terms of the underlying estimated CRRA. This result is substantially different from the findings by Brañas-Garza et al. (2018) using a large sample of students in London: in our representative sample of the UK population we do not replicate their finding of a significant association between the digit ratios and an experimental measure of risk aversion.

Third, neither the R2D:4D nor the L2D:4D is significantly associated with the time discounting measures. Our results are in contrast to those of Lucas and Koff (2010) which report that lower digit ratios are correlated with greater discounting among women; and those of Ayciena and Rentschler (2017) which report that lower digit ratios is negatively correlated with discount factor. Our findings however, are closely in line with those of Drichoutis and Nayga Jr (2015) that report no effect on digit ratios on time discounting.

Fourth, there is substantially no interaction between R2D:4D and L2D:4D and female in explaining risk tolerance and time discounting. Some exceptions are that the interaction term between female and R2D:4D is significantly and positively associated with risk aversion as measured and estimated by the HL high task; the interaction term between female and L2D:4D is negatively and significantly associated with risk aversion as measured and estimated by the B-EG task; and that the interaction term between female and L2D:4D is negatively and significantly associated with hyperbolic discounting (1/12 months no-FED).

Overall, our results suggest that, once the links between the digit ratios and behavioural economics measures of risk tolerance and time discounting are systematically assessed and reported in a representative sample of the population, there is very little evidence in support of the hypotheses that digit ratios are significantly associated with individual risk attitudes, risk aversion, implicit discount rates, hyperbolic discounting, and present-bias. Further systematic research is needed to test whether similar null findings generalize to other representative samples.

Chapter 4

Do Health Shocks Affect Smoking? Evidence from the French Gazel Panel Data

This chapter was co-authored
with **Lise Rochaix**.

Summary of the chapter:

This paper investigates the relationship between an acute health shock, namely the first onset of an accident requiring medical care, and smoking, using rich panel data from a large French cohort of electricity board workers. To identify the causal effects of such shocks on smoking, we use a fixed-effects model. Results suggest that there is a significant reduction in smoking consumption. This reduction lasts over 10 years. Throughout this period, individuals subject to such a shock reduce, on average, cigarette consumption by 1.2 units (per week). Further, the findings show heterogeneous effect among smokers: heavy smokers are more likely to reduce tobacco consumption than occasional smokers. Moreover, we investigate the sensibility of our results to other lifestyle outcomes: the health shock has a significant and negative impact on alcohol consumption, but has no effect on Body Mass Index.

Classification:

Keywords: health shocks; panel data; France; Smoking; fixed-effect model

JEL: C23; I10; I12

Acknowledgments:

Lise and I give special thanks to Thomas Barney, Andrew Jones, Célia Lemaire, Jean-Pierre Messe, Alexandre Sauquet and to Carole Treibich.

We also thank all participants of the 13th Doctorissimes (Paris 1 University), of the 16th Louis-André Gérard-Varet, and of the 2017 iHEA. We gratefully acknowledge Noémie Kiefer, Léa Toulemon, Laurie Rachet-Jacquet for their feedbacks on panel data.

The authors express their thanks to EDF-GDF, especially to the Service Général de Médecine de Contrôle, and to the "Caisse centrale d'action sociale du personnel des industries électrique et gazière". We also wish to acknowledge the Cohortes team of the Unit UMS 011 Inserm - Versailles St-Quentin University responsible for the GAZEL data base management. The GAZEL Cohort Study was funded by EDF-GDF and INSERM, and received grants from the "Cohortes Santé TGIR Program", Agence nationale de la recherche (ANR) and Agence francaise de sécurité sanitaire de l'environnement et du travail (AFSSET).

Contents of chapter 4

1. Introduction

This paper asks whether an acute health shocks (i.e. the first onset of an accident requiring medical care) influence smoking behavior, either by reducing tobacco consumptions, by encouraging individuals to stop smoking, or by inciting non-smokers to start smoking. By doing so, this study contributes toward a better understanding of what induces health behavior changes. Drawing on behavior economics, the analysis considers that individuals received information on life's vulnerability when they face harmful health consequences in general. Being afraid of dying, or being injured after the accident, may act as a warning signal indicating that these types of feelings could happen again if the individual did not stop smoking. This signal could be considered as imperfect information on the risk of developing a disease. To circumvent such feelings, or a future (smoking-related) health shock, individuals might stop or reduce smoking.

Acute health shocks may both have beneficial (i.e. reducing tobacco consumption) and detrimental (i.e. increasing tobacco consumption) effects. Regarding beneficial effects, three channels can be defined. First, there may be an increased medical pressure to improve lifestyles through more frequent interactions with health care professionals and/or the urging of family members. Second, since health shocks are strongly associated with labor market inactivity (Garcia Gomez and Lopez Nicola (2006); Garcia-Gomez (2011); Garcia-Gomez et al. (2013); Jones et al. (2016); Trevisan and Zantomio (2016)), resulting in lower individual and household incomes (Riphahn (1999); Garcia Gomez and Lopez Nicola (2006); Garcia-Gomez et al. (2013)), individuals may decrease unhealthy behaviors due to stringer financial constraints. Third, by modifying making individual more risk averse (e.g. Decker and Schmitz (2016)), acute health shocks may increase individuals' willingness to adopt healthier behaviors. Regarding detrimental effects, two channels can be defined. First, individuals facing post-traumatic stress and/or fear due to reduced life expectancy (Op den Velde et al. (2002); Kelly et al. (2015)) may increase unhealthy behaviors. Second, by modifying time preferences (e.g. making individuals more present-oriented), negative health shocks may also increase unhealthy behaviors. Determining the direction and the magnitude of the effects of health shocks on lifestyles is thus a complex empirical issue.

Empirical evidence supports the existence of a significant and positive relationship between health shocks and health behaviors. Health shocks lead to smoking reduction among British adults (Clark and Etilé (2002)), for middle aged and retired Americans (Falba (2005); Khwaja et al. (2006); Keenan (2009)), for ageing Germans (Hsieh (1998))[89], and for Taiwanese individuals (Hsieh (1998)). Further, smokers differ from persons who do not smoke in how information influences their longevity expectations. Smokers experiencing a health shock interpret this information as reducing their chances of living to age 75 or more (Smith et al. (2001)). Additionally, covariate health shocks (i.e. affecting a whole population, such as the H1N1 influenza pandemic) improve hand-washing frequency for Mexican persons (e.g. Agüero and Beleche (2017)). Theoretical foundations have been offered for these behavioral changes, based on demand for health models (e.g. Grossman (1972)) or on learning models (e.g. Viscusi (1992); Liu and Hsieh (1995)). These models are constructed on three assumptions. irst, health shocks are assumed to be directly related to individuals' lifestyles. Second, individuals have minimum knowledge to link health deteriorations to their health behaviors. Third, individuals know effective ways to change their behaviors to improve their health[90]. In this study, the last two assumptions hold, but we relax the first one, in that health shocks may be independent of lifestyles.

We use a rich French panel data (*Gazel*[91]), which covers 20,000 individuals (15,000 men and 5,000 women) working for the French national electricity board (EDF-GDF) over the 1989 to 2014 period. Using this yearly panel data highlights both inter-individual differences and intra-individual dynamics and helps capture part of the complexity of decisions in this domain. Further, we compare the outcomes of individuals who had only one single shock over this period with those that never had any shock. This allows us to concentrate only on acute health shocks and to select out individuals with more than one shock, as they are likely to suffer from chronic diseases.

To identify the causal effect of the health shock on smoking, a fixed-effects model is performed. Specifically, individual fixed-effects capture unobserved time-invariant individual characteristics (e.g. race, genetic factors, or innate ability). Year fixed-effects control for

[89]The same results do to not seem to hold for Body Mass Index as also shown by Sundmacher (2012).

[90]To see more on theoretical model on addiction, please refer to Jones (1989); Chaloupka (1991); Chaloupka and Wechsler (1997); Loonis (2001); Dupilet et al. (2002); Etilé (2004); Kopp and Fenoglio (2011); Laporte et al. (2016). Further, Clark and Etilé (2002) define a model which assumes that individuals also learn over time from non-personal experiences (spouse or friends facing a shock (see also Bala and Goyal (1998); Jones (1994)).

[91]See more on: `http://www.gazel.inserm.fr/en/`, and on Goldberg et al. (2006).

unobserved individual-invariant time effects (e.g. cigarettes' relative prices, or anti-smoking campaign exposures[92]). Further, we test the impact of health shocks on cigarette consumption, on tobacco consumption (i.e. cigarettes, cigars, cigarillos, and pipes), and on the probability to stop smoking cigarettes. We also examine the robustness of our results to other lifestyle outcomes: drinking pattern and Body Mass Index (BMI).

Results suggest that there is a significant effect running from the shock to the number of cigarettes and tobacco units smoked, with impact duration of ten years after the shock. Throughout this period, individuals subject to such a shock smoke on average 1.2 cigarettes and 1.5 units of tobacco less per week. Further, heavy smokers react more than occasional smokers to this shock. Individuals facing shocks also reduce their alcohol consumption. This reduction lasts one year after the shock. They decrease their alcohol consumption by 0.5 glasses per week. We do not find, however, any effect of health shocks on BMI.

This paper improves upon the existing literature in three ways. First, the *Gazel* panel data contains very rich and precise information on health conditions. It constitutes a 25 years follow-up that is of first importance to study addiction patterns. Second, the measure of health shock, i.e. the first onset of an accident requiring medical care, is comparatively less noisy than previously used measures, with less severe endogeneity issues. Facing an accident is more exogenous than a serious decline in self-reported health status (Garcia-Gomez (2011); Sundmacher (2012)), or a drop in the level of health satisfaction (Riphahn (1999)). These measures might reflect very different health situations (e.g. chronic or acute health shocks, physical or psychological health deteriorations). Further, accidents may be less subject to reverse causality than the onset of a heart attack (Smith et al. (2001); Clark and Etilé (2002); Sahm (2012)), which could be partly the consequence of individuals' lifestyles. Third, by estimating the impact, on French data, of health shocks on lifestyles and the duration of its effect. To the best of our knowledge, we are the first to test these three lifestyle outcomes for a given population.

The paper proceeds as follows. Section 2 describes the data. Section 3 presents our empirical strategy. Section 4 shows the results and reports the quality of the identification

[92]Smoking in France was first restricted on public transport by the Loi Veil launched in 1976. Further restrictions were established in 1991 due to the Loi Evin. This law contains a variety of measures against alcoholism and tobacco consumption. On February 2007 smoking is ban from public places, such as offices, schools or restaurants. For a discussion on ban effects on smokers, see De Chaisemartin et al. (2011) and Jones et al. (2015).

strategy through the robustness checks. Section 5 discusses the findings. The last section concludes and highlights avenues for future research.

2. Data

Gazel's main purpose is to develop longitudinal epidemiological information on health-related issues. This dataset is a yearly panel with approximately 20,000 individuals throughout all regions of France. It provides 25 waves of individual data on health status, lifestyles, socioeconomic and occupational factors collected via a standardized questionnaire. This questionnaire is sent yearly by mail to all participants. The cohort was set up in January 1989, with an invitation to participate sent to all GDF-EDF male employees aged 40 to 50, and to all female employees aged 35 to 50. Invitation letters only mentioned participation to a long-term health study to improve medical research. Attrition rates are very low: less than 5% of the cohort had died (861 men, and 155 women) by the end of 2005 and only 126 subjects (0.6%) had dropped out during the first 17 years of follow-up (1989-2005). Using this dataset contributes to better understand addiction patterns as it provides very rich information on smoking and drinking behavior over a long period. Further, by using *Gazel*'s data we are able to match on a large number of covariates to remove confounding factors.

2.1. Variables of interest

To measure the health shock, we rely on the first onset of an accident requiring medical care, over the whole span of the panel. To do so, we use the following question: "Over the last twelve months, have you ever had accidents that led to medical care use?". Although our measure of health shock does not provide information as to which type of health event an individual is facing - which constitutes a clear limitation of our study - we might be able to assume that such shocks refer to a labor market accident or a traffic accident. Indeed, the question contains a note indicating that the health shock could be, for example and among others, a labor market accident or a traffic accident. In order to focus on acute shocks, we select out individuals with more than one shock as they are likely to suffer from chronic diseases.

To measure smoking pattern, we rely on tobacco and cigarette consumption. Tobacco consumption is defined as the total number of tobacco units smoked per day, ranging from 0 to 90. Specifically, we use the following question: "How many cigarettes/pipes/cigarillos/cigars do you smoke per day?" By doing so, we can precisely assess the potential change in the number of tobacco units smoked per day. Cigarette consumption is defined using the same question, but focusing only on cigarettes (the number of observations for pipes, cigarillos and cigars is not important enough to make a separate analysis). We also compute a dummy variable equals to one for heavy smokers (i.e. individuals smoking more than 20 cigarettes per day), and zero otherwise.

To assess the sensibility of our results on smoking, we rely on two other lifestyle outcomes: alcohol and BMI. Alcohol consumption is defined as the total number of glasses of alcohol drank (i.e. wine, beer, cider, and spirits) per day. BMI is computed using the self-reported height (in centimeters) and weight (in kilograms). For these two variables, we also compute dummy variables, respectively: 1/ Being at risk for alcohol, i.e. drinking more than 3 glasses per day for men and more than two glasses per day for women, and zero otherwise; 2/ Being at risk of being overweight (or obese), i.e. for BMI over 25 and 0 otherwise[93].

We exploit the richness of the panel by using a broad set of covariates , in particular, age, gender[94], monthly net household income[95], father's profession[96], individual educational attainment[97], occupational status[98], marital status[99], and self-reported health[100].

[93]See more on the French National Authority for Health which provides useful guidelines on lifestyles: See more on: https://www.has-sante.fr/portail/upload/docs/application/pdf/2014-12/outil_rpib_v2.pdf and on: https://www.has-sante.fr/portail/upload/docs/application/pdf/201109/2011_09_30_obesite_adulte_argumentaire.pdf

[94]Gender is a dummy with value one for women and zero for men.

[95]Income is an index ranging from one (the poorest) to 7 (the richest). More precisely: 1 stands for "earn less than 7,500F"; 2 for "earn more than 7,500 but less than 9,000F"; 3 for "earn more than 9,000 but less than 10,500F"; 4 for "earn more than 10,500 but less than 13,000F"; 5 for "earn more than 13,000 but less than 17,000F"; 6 for "earn more than 17,000 but less than 25,000F"; 7 for "earn 25,000F or more".

[96]Father's profession contains seven measures. Specifically, 1 stands for farmers; 2 for craftsman; 3 for chief executive officer or for executive; 4 for intermediary profession; 5 for employee; 6 for worker and 7 for other professions.

[97]Individual level of education is coded as follow: 0 for "lower than high school degree"; 1 for "equals or higher than high school degree".

[98]Occupation status equals to 1 if the individual is employed; 2 if the individual is in sick leave or retired but still working; 3 if the individual is retired.

[99]Marital status is coded as follow: 0 stands for not being in a relationship; 1 for being in a relationship

[100]Individuals who identify themselves as in very good health are coded 1 and those in very bad health are coded 8. Answers rank from 1 to 8.

2.2. Descriptive statistics

We observe 14,127 individuals in our unbalanced panel. In this sample, 27% of the participants are female (n=3,847) and 73% are male (n=10,280). There is a larger proportion of individuals with low educational attainment as 74% (n=10,453) do not have a high school degree. Individuals' father professions are also more likely to be blue collars (32%), compared to white collars (6.5%). Although marital and professional status evolve over one's lifetime, individuals mostly report being in a stable relationship (n=13,298), and are currently working (n=13,945) during the period of analysis. Lifestyles also change both between and within individuals; but they mostly report smoking less than 10 units of tobacco per day and drink between two and three glasses of alcohol per day. Half of the respondent report having a BMI higher than 25, and the other half a BMI lower than 25. Finally, there are 4,818 (34.10%) individuals facing an acute health shocks. More descriptive statistics can be found in Tables A and B in the Appendix Section.

Table 1 describes individual characteristics between the treatment and the control groups. It shows some discrepancies between these groups mainly for professional status, and age. Individuals facing health shocks are less likely to work, and are older than individuals who do not face such shocks. Other characteristics seem to be equally represented between both groups (e.g. father's profession, educational attainment, income, marital status, self-reported health, and gender). Further, individuals in the treatment group declare smoking less (both in term of units of tobacco smoked and in the number of cigarette consumed), than individuals in the control group.

Regarding the national representativeness of our sample, we first identify discrepancies in gender (27% women in our sample compared to 51% in 1989 in France) and education level (for the same year, 24.2% of the French population does not have a high school degree compared to 74% in our sample)[101]. Second, individuals working in a public firm, like EDF-GDF, represent only 20% of total employment in France[102]. Third, the unemployed represent 10.3% of the French population[103], and we have none in our sample. This constitutes the most important limitation of the data as unemployment has been shown to be positively correlated with bad lifestyles (Lee et al. (1991); Novo et al. (2000); Jusot et al. (2008);

[101] See more on: https://www.insee.fr/fr/statistiques/1893182
[102] See more on: https://www.fonction-publique.gouv.fr/fonction-publique-france
[103] See more on: https://www.insee.fr/fr/statistiques/2873744?sommaire=2873834&geo=FE-1

Arcaya et al. (2014)). These selection issues therefore limit the external validity of our results.

Table 1: Characteristics of sample by groups

	Individuals facing health shocks	Individuals who do not face health shocks
	N = 115,120 & n = 4,818	N = 210,024 & n = 9,309
Father is worker	0.310	0.316
	(0.463)	(0.465)
Education attainment	0.262	0.261
	(0.440)	(0.439)
Marital status	0.866	0.882
	(0.340)	(0.322)
Income		
Less than 7,500F	0.029	0.036
	(0.168)	(0.187)
7,500 to less than 9,000F	0.072	0.075
	(0.258)	(0.262)
9,000 to less than 10,500F	0.076	0.084
	(0.265)	(0.278)
10,500 to less than 13,000F	0.193	0.189
	(0.395)	(0.189)
13,000 to less than 17,000F	0.232	0.236
	(0.422)	(0.425)
17,000 to less than 25,000F	0.273	0.265
	(0.445)	(0.441)
25,000 and more	0.123	0.114
	(0.329)	(0.318)
Currently working	0.514	0.609
	(0.500)	(0.488)
Self-reported health	3.283	3.199
	(1.296)	(1.288)
Female	0.274	0.274
	(0.446)	(0.446)
Age	56.143	55.989
	(8.175)	(8.165)
Cigarette consumption	8.632	9.369
	(11.301)	(11.578)
Tobacco consumption	7.972	8.051
	(11.069)	(11.156)

3. Empirical strategy

3.1. Empirical model

We aim at estimating the impact of negative health shocks on lifestyles. Yet, the treated individuals have some specific characteristics not shared with those of the control group, as identified in Table 1. Treated individuals are more likely to be older, and are less likely to work. Furthermore, since our measure of shock focuses on work or traffic accidents, only those with a private mode of transportation will be concerned by the latter[104]. Second, blue and white collars do not have the same probability to face work accident[105]. Clearly, the probability for these individuals to face such a shocks is not random. Taking into account the non-randomness of the occurrence of health shocks calls for a quasi-experimental design. Such will be the empirical strategy adopted here, with a fixed-effects model.

Fixed-effects refer to both individual and time fixed-effects. By using this method, we remove both unobservable individual specific effects that are constant over time (e.g. race, genetic factors, or innate ability), and common time effects such as price variations due to prevention policies. In France, for instance, since the mid-nineties, tobacco prices have more than doubled and since price elasticity of younger and older individuals are comparably higher, this must be explicitly taken into account. This method is similar to several papers in the health economics literature (e.g. Laporte and Windmeijer (2005); Chandra et al. (2010); Duggan and Scott Morton (2010); Hotz and Xiao (2011); Fang and Gavazza (2011); Dafny

[104] In 2012, on average, 80,7% of French households had at least one car. But the rate is lower for large cities: for instance, Paris has a rate of 38%, Marseille 41% and Lyon 59,7%. See more on: http://map.datafrance.info/transport?coords.lat=46.882723010671945&coords.lng=0.24169921874999997&zoom=6&d.d1.id=accidents-de-la-route&d.d1.gr=marker&d.d1.y=2012&d.d1.gp=date&d.d1.f=gravite&d.d1.on=1&d.d1.slug=d1&d.d1.fl=,1,2). These areas are also negatively correlated with the severity (defined as injured individuals requiring hospitalization) of the accident (see more on: http://map.datafrance.info/logement?coords.lat=46.882723010671945&coords.lng=0.24169921874999997&zoom=6&d.d2.id=menages-ayant-au-moins-une-voiture&d.d2.gr=iris&d.d2.y=2010&d.d2.gp=part-des-menages-disposant-d-au-moins-une-voiture&d.d2.on=1&d.d2.slug=d2;). However, Ile-de-France, PACA, and Rhône-Alpes regions gather 38% all motorbikes in France (see more on: http://www.statistiques.developpement-durable.gouv.fr/fileadmin/documents/Produits_editoriaux/Publications/Chiffres_et_statistiques/2013/chiffres-stats400-deux-roues-motorises-au-01012012-mars2013.pdf), and face more sever accident than cars (see more on: http://www.driea.ile-de-france.developpement-durable.gouv.fr/accidentologie-deux-roues-motorises-en-ile-de-a1519.html). These figures show that even if there's heterogeneity in the type of private mode of transportation used, individuals in Ile-de-France, PACA and Rhône-Alpes may be more likely to face severe shocks.

[105] Skilled blue collars are more likely to face a work accident than white collars (see more on: http://www.statistiques.public.lu/stat/ebook/Regards052014/files/assets/basic-html/page1.html).

et al. (2012); de Chaisemartin and D'Haultfœuille (2016)).

Specifically, we use the following model (1):

$$Smoking_{i,t} = \beta.(Health\ Shock_{i,t}) + \tau.X'_{it} + \gamma_i + \gamma_t + \epsilon_{i,t} \tag{1}$$

Where $Smoking_{i,t}$ is the main outcome variable (total number of unit of tobacco consumed, or total number of cigarettes consumed) for individual i at time t; $Health\ Shock_{i,t}$ is a dummy variable set to 1 for years after the shock for individuals in the treatment group, 0 otherwise; X'_{it} is the covariate matrix (detailed in the previous Section); γ_i are individual fixed-effects; γ_t are time fixed-effects; and $\epsilon_{i,t}$ is an error term that is assumed to be orthogonal to all characteristics.

Further, to analyze how long lasts the effect of health shocks on smoking[106], we compare the evolution of cigarette consumption for the treated and the control groups over the period of analysis. More precisely, we compare the consumption of cigarette consumption 5 years before the occurrence of shocks up to 10 years after. We specifically compare the mean of cigarette consumption for both group, choosing the year before the shock (i.e. $t = -1$) as reference. We, therefore, are able to analysis whether cigarette consumption have increase or decrease over years by comparison with the consumption in $t = -1$.

3.2. Identification

Our identification approach exploits the probability that an individual may face one or more accidents. The focus on this specific type of health events is motivated by the fact that they are, in most cases, unanticipated. Even in the case individuals might envisage experiencing a similar health shock, uncertainty remains, if not on occurence, on the time of potential occurence. Previous works on the relationship health and labor market behaviors have adopted similar measures (e.g. Garcia Gomez and Lopez Nicola (2006)).

For β to measure the causal impact of health shocks on smoking, there should be no endogeneity issues. We are not able, however, to provide with certainty that this is not the case. Endogeneity issues may appear if health shocks and smoking are both correlated with unobservable variables. For example, personality traits (e.g. conscientiousness, extraversion)

[106] We did the samke for alcohol consumption and BMI in the robustness checks Section.

may influence both smoking and the probability to face a shock. Further, self-reported measures of tobacco may suffer from desirability bias, leading to measurement errors. More specifically, self-reported data on the consumption of cigarettes, tobacco and illegal drugs likely contain errors (Hoyt and Chaloupka (1994)). In the case of cigarettes, there are two difficulties. First, obtaining an accurate figure of daily consumption. Second, we are not able to control for the possibility that another household member is present when the respondent is answering the questionnaire. The first bias appears clearly when we look at the distribution of daily cigarette consumption in our estimate sample, as shown in Figure 1 and Table 2.

Additionally, we are not able to know with certainty that the health shock variable refers to a traffic or a labor market accident. Indeed, 34% of our sample report facing such type of shocks. In the French population, however, such figure falls to 3% in 1989 (year of inclusion), to 2.26% in 2007, and to 1.09% in 2014[107]. Two reasons might explain why we have such differences. First, the sample under consideration in this chapter is mainly low socio-economic groups, which are at higher risk of facing traffic and labor market accidents. Second, as mentioned earlier, the following questions might induce the reason of the accidents, but if a large proportion of subjects respond "no" to either labor market accident and to traffic accidents, it means that the source of the accident is unknown.

It is worth noticing, however, that this last point does not threaten our empirical strategy as individuals may refer to other type of accidents, such as a domestic accident, a sport accident, an every-day life accident (e.g. a fall in the street), or a cerebro-vascular accident. All of them could be, to un certain extent, assumed not to be anticipated.

[107]See more on: https://www.ladocumentationfrancaise.fr/var/storage/rapports-publics/094000007.pdf and https://www.insee.fr/fr/statistiques/1906693?sommaire=1906743.

Figure 1: Number of cigarettes smoked per day

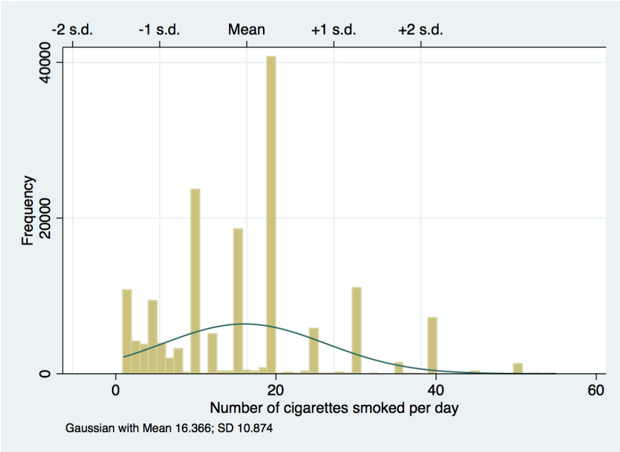


Table 2: Number of cigarettes smoked

	Frequency (1)	Percentage (2)	Cumulative % (3)
Number of cigarettes smoked per day			
1	4,593	2.95	2.95
2	6,099	3.92	6.88
3	4,180	2.69	9.57
4	3,657	2.35	11.92
5	9,276	5.97	17.89
Between 6 and 9	9,084	5.85	23.74
10	23,653	15.22	38.95
Between 11 and 14	5,771	3.71	42.67
15	18,589	11.96	54.62
Between 15 and 19	1335	0.87	55.55
20	40,656	26.15	81.63
Between 21 and 24	495	0.33	81.98
25	5,821	3.74	85.69
Between 26 and 29	107	0.08	85.77
30	10,921	7.03	92.78
Between 31 and 40	1344	0.87	93.65
40	7,099	4.57	98.22
Over 41	2,774	1.79	100
Total	155,454	100	

Smokers seem to have difficulty in evaluating precisely their daily consumption, and base their replies on the obvious fractions and multiples of a packet. This bias is equally found in year-to-year changes in cigarette consumption, as shown in Figure 2 and Table 3. For the second bias, there is no way to know whether or not other persons surrounded the individual when answering the questionnaire.

Figure 2: Yearly change in number of cigarettes smoked

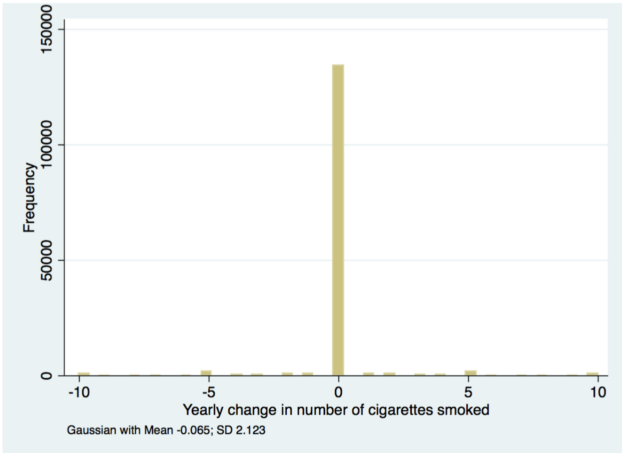


Table 3: Yearly change in number of cigarette smoked

	Frequency (1)	Percentage (2)	Cumulative % (3)
Year-to-year change in number of cigarettes smoked per day			
Reduction of more than 10 cigarettes	684	0.46	0.46
10 cigarettes less	845	0.57	1.03
Between 9 and 6 less cigarettes	429	0.28	1.31
5 cigarettes less	2,062	1.39	2.71
Between 4 and 1 less cigarettes	2,559	1.73	4.44
No change	142,798	91.46	95.90
Between 1 and 4 more cigarettes	2,723	1.84	97.74
5 cigarettes more	2,027	1.37	99.10
Between 6 and 9 more cigarettes	317	0.22	99.32
10 cigarettes more	707	0.48	99.80
Increase of more than 10 cigarettes	303	0.20	100
Total	155,454	100	

4. Results

4.1. Main results

Table 4 shows the effect of health shocks on smoking using the fixed-effect model described in equation (1). We report results as follows. Column 1 gives the difference between the treated and control groups in the average number of cigarettes smoked without individual covariates, time fixed-effects, and individual fixed-effects. Column 2 provides results of column 1 adding individual covariates. Column 3 and 4 add respectively time fixed-effects and individual fixed-effects. Table 5 is organized in the same manner, but analyzes the impact of health shocks on tobacco consumption and on the probability to smoke.

Table 4: Impact of health shocks
on cigarette consumption

	(1)	(2)	(3)	(4)
	Nb. cigarettes	Nb. cigarettes	Nb. cigarettes	Nb. cigarettes
Health Shocks	-0.650***	-0.185***	-0.174***	-0.175***
	(0.018)	(0.020)	(0.020)	(0.020)
Individual controls	No	Yes	Yes	Yes
Time fixed-effects	No	No	Yes	Yes
Individual fixed-effects	No	No	No	Yes
Observations	279,665	279,665	279,665	279,665
No. of individuals	14015	14015	14015	14015
Overall-R^2	0.000	0.009	0.010	0.005

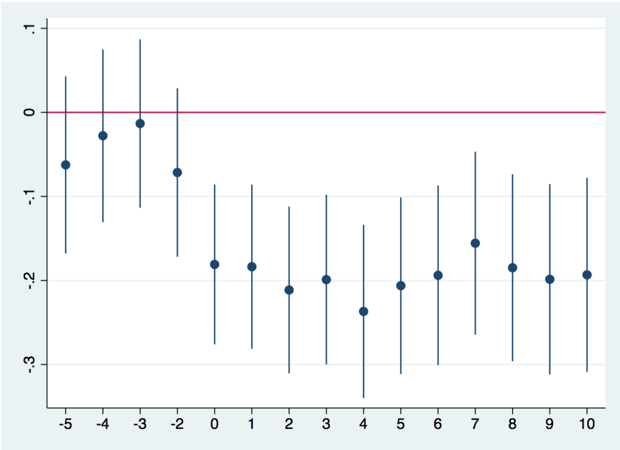
Table 5: Impact of health shocks
on tobacco consumption and the probability to smoke

	(1) Nb. tobacco units	(2) Nb. tobacco units	(3) Pr(smoke)	(4) Pr(smoke)
Health Shocks	-0.214***	-0.218***	-0.041***	-0.028***
	(0.018)	(0.018)	(0.002)	(0.002)
Individual controls	Yes	Yes	Yes	Yes
Time fixed-effects	Yes	Yes	Yes	Yes
Individual fixed-effects	No	Yes	No	Yes
Observations	324,749	324,749	324,749	324,749
No. of individuals	14,115	14,115	14,115	14,115
Overall-R^2	0.007	0.004	0.019	0.096

Compared to those who do not face a health shock, treated individuals reduce both their cigarette consumption (by 1.2 cigarettes) and their tobacco consumption (by 1.5 units).

Figure 3 provides the effect of health shock on cigarette consumption over time. Figure 3 shows that individuals facing health shocks reduce their cigarette consumption over 10 years. More precisely, they reduce significantly the number of cigarette smoked per day after the shock by comparison with the number of cigarette smoked one year before its occurrence.

Figure 3: Effect of health on cigarette consumption over time



4.2. Robustness checks

To test the robustness of our results, we rely on two other lifestyle outcomes: alcohol and BMI.

Alcohol and BMI are used to check if other health behaviors have changed after facing a health shock. By using these variables, we are able to document whether the health-promoting effect of the health shock occurs only on one type of health behavior, or if it occurs in a more general setting. All the three variables (tobacco, alcohol and BMI) can may be grouped into one more generic term: health preferences. If the health shock also reduces alcohol consumption and improves BMI, it may be hypothesized that the health shock have improved the individuals' health preferences.

Column 1 of Table 6 investigates the effect of health shocks on alcohol consumption, column 2 investigates such effect on being at risk for alcohol, column 3 gives the impact of health shock on BMI, and column 4 when being at risk of overweight. All columns control for individual covariates, time and individual fixed-effects. Individuals facing a health shock are more likely to reduce alcohol consumption, but no effect is found for those being at risk for alcohol consumption. The effect of the shock has no impact on BMI, on average, but has an impact for those being at risk of overweight.

While facing a health shock reduces the number of units of tobacco smoked on average, significant disparities may exist in the population and need to be further documented. To study heterogeneous effects, we compare occasional and heavy smokers, the former being defined as smoking at most 5 units of tobacco smoked per day and the latter at least 20 units of tobacco smoked per day. The results (column 5 of Table 6) show that heavy smokers are more likely to reduce their cigarette consumption, compared to occasional smokers, for whom no significant effect was found.

Table 6: Robustness checks:
Impact of health shock on alcohol, Body Mass Index, and on heavy smokers

	Alcohol	Alcohol	BMI	BMI	Cigarettes
	(1)	(2)	(3)	(4)	(5)
Health Shocks	-0.067***	-0.041***	-0.022	-0.144***	-0.068***
	(0.009)	(0.008)	(0.014)	(0.017)	(0.016)
Being at risk		2.061***		1.819***	11.878***
		(0.005)		(0.012)	(0.027)
Health Shocks × Being at risk		0.006		0.242***	-0.102***
		(0.009)		(0.019)	(0.031)
Individual controls	Yes	Yes	Yes	Yes	Yes
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Individual fixed-effects	Yes	Yes	Yes	Yes	Yes
Observations	252851	252851	156290	156290	279665
No. of individuals	12368	12368	13150	13150	14,015
Overall-R^2	0.008	0.639	0.010	0.511	0.691

Figures 4 and 5 provide the effect of health shocks on alcohol consumption and BMI over time. Individuals who faced a health shock reduce the number of glass of alcohol drank only one year after the shock. There is no effect of such shocks on BMI.

Figure 4: Effect of health on alcohol consumption over time

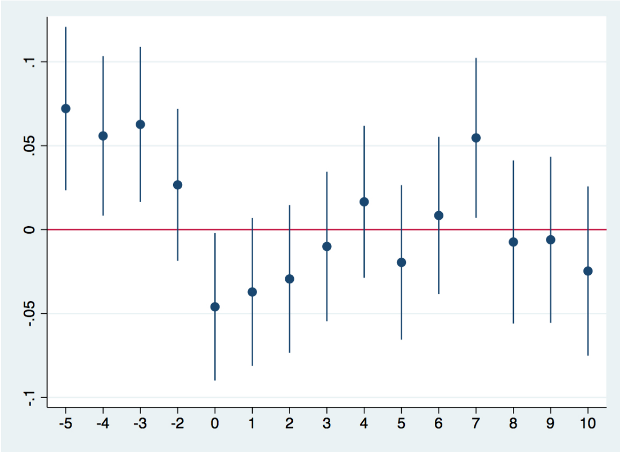
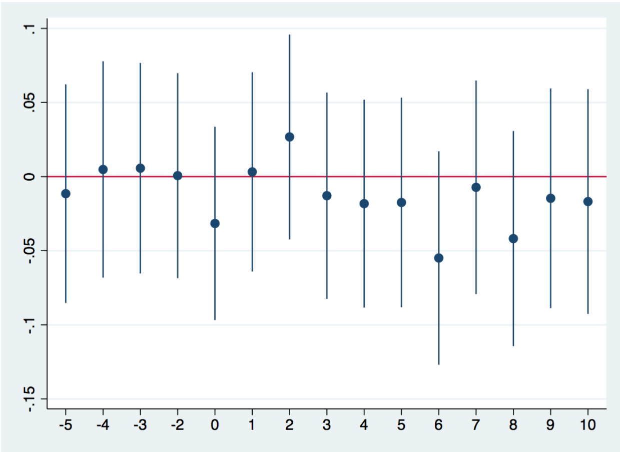


Figure 5: Effect of health on Body Mass Index over time



Overall, our results are robust, which indicates that the effects identified can be reasonably attributed to the health shock experienced.

5. Discussion

We offer three possible mechanisms that constitute plausible explanations of our results and reasons why shocks seem to affect lifestyles differently through time.

First, improving lifestyles involves short-term costs (e.g. psychological or physical costs, motivation costs, financial costs) and long-term benefits (e.g. increasing life expectancy, quality of life improvement, reduced financial burden). Before the occurrence of health shocks, individuals might put higher weight on short-term rather than on long-term benefits[108], leading them to adopt bad lifestyles. The benefit of changing their habits becomes, however, more important once the shock occurs. By modifying individual time preferences (i.e. the degree to which one values the future more than the present), acute health shocks increase the value of future health. This drives individuals to weigh long-term benefits more than short-term costs and to invest in health by adopting better lifestyles, in accordance with the human capital approach defined by Grossman (1972).

Second, health shocks may also increase individuals' risk aversion (e.g. Decker and Schmitz (2016); Kokot (2017)) leading them to be more cautious with their health. Risk averse individuals have been found to be more sensitive to preventive or information campaigns, and to exhibit improved health behaviors (Picone (2004); Harrison et al. (2015); Van Der Pol et al. (2017); Galizzi and Miraldo (2017)). After health shocks, therefore, individuals can improve lifestyles due to an increased risk aversion.

Third, individuals may, however, change their lifestyles only if they believe they can control their health outcomes through their behavior. Several studies have indeed shown that individuals with a high internal locus of control (i.e. the degree to which individuals believe they have control over the outcome of events in their life, as defined by Roter, 1954) are more likely to adopt healthier lifestyles (Cobb-Clark and Schurer (2013); Cobb-Clark et al. (2014); Mendolia and Walker (2014); Conell-Price and Jamison (2015)). In our case, health shocks may have improved individuals' perception of control, leading them to adopt healthier lifestyles.

Additionally, our results show that the health shocks lead to reduce smoking and alcohol consumption. This is consistent with both the Grossman model of health demand and with the learning about health consequences model. In the Grossman model of health demand, tobacco consumption is an input into the health production function. In such setting, future health status is the sum of initial health (which is assumed to be fixed), plus all past health changes and the gross health investment. The effect of a health shock can be plug in this model as an exogenous variation of the health status. To compensate for this decrease, individuals can reduce his or her current tobacco consumption. Indeed, as both

[108] Previous papers found significant associations between time preference and smoking (see for example Scharff and Viscusi (2011)).

smoking and health investments are inputs into health production function, the two could be interconnected: reducing tobacco consumption may compensate a worsening of health.

In this model, all relevant parameters are assumed to be known and constant. An alternative model – the learning about health consequences model – considers that not all of these parameters are known with certainty and that the variation of the health status is likely to be idiosyncratic. As a results, Duesenberry et al. (1949) and Clark and Etilé (2002) propose a setting in which the consumption of an addictive good can be reduced by new information about the negative consequences of such good. In this model, tobacco consumption will be reduced if smokers observe harmful health consequences of their smoking. In our setting, we assume that smokers can also received information on life's vulnerability if they face harmful health consequences in general.

The two models predict a negative correlation between current tobacco consumption and health shocks. This is consistent with our findings. However, without information on individuals' beliefs, we can't distinguish between the two models.

Our results on the persistence of the reduction effect are in line with other international studies. In the US, in the UK, and in Denmark heavy smokers are more likely to remain abstinent after trying to stop smoking than occasional smokers (Burns (2000); Godtfredsen et al. (2001); Kotz et al. (2012)). This may be because heavy smokers receive more advice from their GP than occasional smokers (Kotz et al. (2013)). Two reasons may be offered to explain the comparatively lower persistence of our alcohol and BMI's results. First, physicians feel less trained to advise about alcohol and fat foods consumption than smoking cessation, and believe that more time is required for diet change than cigarette change (Dolor et al. (2010)). Second, social norms regarding body shape and weight may also explain why BMI has not changed (Burke and Heiland (2007)). Etilé (2007) finds that having an ideal BMI in mind predict attitude towards eating habits, and that social norms regarding body shape have significant effects on BMI only for women who want to lose weight.

Further, our findings contribute to a growing literature questioning the assumption of time invariant health preferences (Craig et al. (2014); Ami et al. (2017); Bunn et al. (2006); Masanja et al. (2012)). Health preferences here refer to the individuals' willingness to adopt healthy behaviors. Smokers could therefore be seen as individuals with low health preferences. If health preferences were stable over time, then smokers would not reduce their cigarette consumption after a shock. As we observe the opposite, this gives some support to the hypothesis of non-stable preferences.

Our results do not lead to straightforward policy implications as health shocks cannot be replicated within a preventive strategy relying on nudges. In fact, the question of whether acute health shocks constitute a nudge *per se* has been addressed recently (Agüero and Beleche (2017)). Because the occurrence of such a shock is not decided by a third party, it seems more appropriate to associate a health shock with the provision of negative information rather than a nudge. Our results suggest such health shocks, by providing negative information, are instrumental in changing health behaviors, particularly for the heavy smokers. This corroborates results by Moorman and van den Putte (2008) who have shown that when nicotine dependence and quitting intention are both high, negative information works better. Previous results in prevention have also shown that negatively framed information promotes breast-self examination (Meyerowitz and Chaiken (1987)), breast screening (Edwards et al. (2001)), and the early detection of a disease (Rothman et al. (2006)). More recently, e-cigarette smokers have been shown to be more sensitive to loss-framing health risks than non-smokers (Kong et al. (2016)).

6. Conclusion

The paper offers informative evidence on how French workers from the national Gaz and Electricity board have changed their lifestyles following an acute health shock. The findings suggest that there is a significant effect running from the shock to the number of units of tobacco smoked, and to the number of glasses of alcohol drank. There is no effect, however, on BMI. These reductions last over ten, and one years respectively. Throughout these periods, individuals subject to such a shock reduce, on average, cigarette consumption by 1.2 units, and alcohol consumption by 0.5 glasses (per week). Further, heavy smokers are more likely to reduce tobacco consumption than occasional smokers. We also find here that individuals do not seem to display time-invariant health preferences.

Our results, nonetheless, face external and internal validity limitations. External limitation is related to the fact that the sample is not representative of the French population, as documented in the descriptive statistics section. Internal validity limitation is due to unobserved heterogeneity. Other unobserved factors are likely to influence individuals' lifestyles. Such factors could be the partner's smoking status (Clark and Etile (2006); Khwaja et al. (2006); Rocco and d'Hombres (2014)), social interactions (Jones (1994); Poutvaara and Siemers (2008); Eisenberg et al. (2014)), and parents' time and risk preferences (Brown and van der Pol (2014)). Further concerns emerge as data does not allow a precise measurement of (medical or perceived) severity and does not identify the type of shock. Our results may not be, therefore, generalizable to other shocks.

Bearing in mind the special nature of the health shock discussed above, the policy implications of our research suggest designing information campaigns that are as close as possible to individuals' own experiences, mimicking the effects of health shocks or relying on peers' experience sharing. This would be in line with other recent empirical studies showing that emotional contained information – such as reciprocity or active perspective-taking – reduce discrimination against Muslim (Tusicisny (2017)) and transphobia (Broockman and Kalla (2016)) respectively[109].

Likewise, our results seem to emphasize the fact that the time at which information is released matters. Indeed, individuals may be more sensitive to preventive information once they have experienced a negative health shock. Policy makers can try to deliver information on smokers that had health shocks as their are more likely to reduce their consumption. This may lead to a permanent cessation of smoking. Yet the present analysis cannot inform as to the individual's motivation behind the decision to reduce or stop smoking. To do so, detailed information on individuals' preferences would be needed here, such as that collected on a regular basis in the innovation panel of the UK Understanding Society panel. This would help identify the precise pathways that influence these complex decisions.

[109] Another possible illustration could be the recent Uruguay campaign where pictures of newborn defects were shown on cigarette packs, in order to induce future mothers to quit smoking (Harris et al. (2015)).

7. Appendix

Table A1: Impact of health shocks on smoking consumption

	Cat. smoking 5 cig. increments (9 cat.)	Cat. smoking 5 cig. increments (5 cat.)	Cat. smoking With non-smokers	Full pack (20 cig.)	Half pack (10 cig.)
	(1)	(2)	(3)	(4)	(5)
Health Shocks	-0.056***	-0.045***	-0.027***	-0.006***	-0.025***
	(0.006)	(0.005)	(0.003)	(0.001)	(0.003)
Control variables	Yes	Yes	Yes	Yes	Yes
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Individual fixed-effects	Yes	Yes	Yes	Yes	Yes
Observations	155,446	155,446	279,651	155,304	152,674
No. of individuals	7,325	7,325	14,015	7,319	7,209
Overall-R^2	0.006	0.007	0.003	0.002	0.005

General Conclusion

Individual behaviors play a central role in the chronic disease burden faced by developed countries. Major health issues, such as lung cancer, hypertension, and diabetes are exacerbated by unhealthy behaviors. For example, tobacco consumption is responsible for 7.2 million deaths every year, sedentary lifestyles and unhealthy diet account for 5.7 million deaths, and alcohol for 3.3 million deaths[110]. Current health policy interventions aiming at behavior change have, therefore, limited impacts as many individuals still have unhealthy behaviors.

In order to improve impact and take-up, interventions are increasingly targeted at subgroups of the population. Beneficiaries are often defined on risk factors (e.g. Rose et al. (2008); McLaren and Petit (2018)) or socio-economic characteristics[111]. More recently, prevention interventions have tailored messages (e.g. loss-framed or gain-framed messages) according to individuals' characteristics (e.g. Kreuter and Skinner (2000); Kreuter and Holt (2001)) to improve beneficiaries' understanding of health messages (e.g. Schmid et al. (2008) and (McLaren and Petit, 2018))[112].

Most of the above-mentioned interventions are, therefore, based on inter-individual characteristics' differences. Beyond these differences, intra-individual variations (either over time or across different settings) also need to be better understood. For instance, why does a man attend his first prostatic screening consultation but not subsequent ones? Why is a woman who attends one type of screening more likely to attend another type? Clearly, individual decision-making has multiple determinants, among which personality traits and preferences, and it is likely that these traits and preferences are not stable over time. If such were the case, instability might well explain the limited effectiveness of existing health interventions.

This PhD dissertation has focused on investigating whether individuals have non-stable traits and preferences, in particular after facing different types of health events. Results from Chapter 1 show that individuals have relatively stable traits. Perception of control, measured with the individual LOC, appears to be quite stable – yet not set in stone as

[110]GBD 2015 Risk Factors Collaborators. Global, regional, and national comparative risk assessment of 79 behavioral, environmental and occupational, and metabolic risks or clusters of risks, 1990–2015: a systematic analysis for the Global Burden of Disease Study 2015. Lancet, 2016; 388(10053):1659-1724.

[111]Other types of interventions exist, such as universal approaches (e.g. mandatory food program, population-wide vaccine campaigns).

[112]The reader can refer to O'Keefe and Jensen (2009) for a meta-analytic review.

some variation is indeed present. And individuals facing a health shock are more likely to reduce their perception of control than others. That is, they tend to believe that their future outcomes are more determined by external factors than their own will. This decrease is attributable to individuals who had, prior to the health event, higher values of LOC.

Results from Chapter 2 show a different pattern: there is no evidence that risk tolerance is significantly affected by past health shocks. Such results are robust across all risk tolerance elicitation methods. Indeed, both self-reported questions and incentive-compatible experimental tasks do not show results that would be significantly associated with past health shocks.

Although risk tolerance does not appear to be determined by health events, biological factors may have played an important role in its determination. Such a research question is investigated in Chapter 3. To do so, we have analyzed whether the digit ratio – a biomarker of prenatal testosterone exposure – is associated with several measures of current risk tolerance (both experimental and self-reported questions). Results show that none of the measures of risk tolerance are significantly associated with the right and the left-hand digit ratios. Risk tolerance is, therefore, unlikely to be determined before birth. We do find the same results for time discounting: both digit ratios are not significantly associated with time discounting.

The fourth Chapter investigates a related research question: does the experience of a health shock modeled health behaviors? Findings indicate that individuals facing health shocks are indeed more likely to reduce their tobacco and alcohol consumption. This effect lasts 5 years for cigarettes consumption, and 3 years of alcohol consumption. Even though the reduction is limited in size (1.2 cigarettes less per week), the duration impact is important. As attempts to stop or reduce smoking last, on average, 2.4 months (e.g. Segan et al. (2006); Herd et al. (2009)), results in this chapter show a duration that is 25 times higher. Health shocks are, therefore, a major determinant of smoking reduction attempts.

Our results may be of relevance for the design of efficient public interventions. Recently, tailored and narrative approaches (i.e. using true stories or experiences from someone else) have been shown to be efficient in reducing Muslim discrimination and trans-phobia (Broockman and Kalla (2016); Tusicisny (2017)). Brief interventions encouraging active consideration of Muslim or transgender individuals through perspective-taking (e.g. "imagining the world from another's vantage point" - Broockman and Kalla (2016), p.2) have significantly reduced prejudices and false-stereotypes. Based on this PhD dissertation results, the same combined strategy of tailored and narrative approaches might prove efficient in promoting health behavior changes. First, we have shown that individuals seem to be sensitive to personalized information delivered when facing a health shock. Second, such sensitivity seems to be more marked for health behaviors and for the perception of control than for risk tolerance.

This PhD dissertation could be extended in several directions.

First, by developing and extending some of the research questions investigated in this PhD in the French context. That is, to analyze whether health shocks have not only modeled risk tolerance, but also time preferences for French individuals. Further, to identify which types of health shocks have the most influence on risk and time preferences. Indeed it is likely that the effect of a health shock might differ, depending of the type of event: individuals facing major health events (e.g. cancer, heart attack, or stroke) are more likely to change their risk tolerance and time preferences than those facing minor events (e.g. diabetes or high blood pressure). Linking a behavior economics questionnaire within the French nationally representative Constances cohort would allow doing so.

Second, by extending some of research questions to other areas of application, such as long-term care since epidemiological and clinical evidence suggests that physical health shocks are more likely to occur at older ages. This would imply studying the impact of physical health shocks on mental health, knowing that these shocks might trigger a new mental health condition or the deterioration of an existing one.

Bibliography

Adams, S. J. (2002). Educational attainment and health: Evidence from a sample of older adults. *Education Economics*, 10(1):97–109.

Affleck, G. and Tennen, H. (1996). Construing benefits from adversity: Adaptotional significance and disposltional underpinnings. *Journal of personality*, 64(4):899–922.

Affleck, G., Tennen, H., Croog, S., and Levine, S. (1987). Causal attribution, perceived benefits, and morbidity after a heart attack: an 8-year study. *Journal of consulting and clinical psychology*, 55(1):29.

Agüero, J. M. and Beleche, T. (2017). Health shocks and their long-lasting impact on health behaviors: Evidence from the 2009 h1n1 pandemic in mexico. *Journal of Health Economics*, 54:40–55.

Akguc, M., Liu, X., Tani, M., and Zimmermann, K. F. (2016). Risk attitudes and migration. *China Economic Review*, 37:166–176.

Allport, G. W. and Odbert, H. S. (1936). Trait names: A psycho lexical study. *Psychological monographs*, 47(1).

Almlund, M., Duckworth, A. L., Heckman, J., and Kautz, T. (2011). Personality psychology and economics. In *Handbook of the Economics of Education*, volume 4, pages 1–181. Elsevier.

Ami, D., Aprahamian, F., and Luchini, S. (2017). Stated preferences and decision-making: Three applications to health. *Revue économique*, 68(3):327–333.

Anderhub, V., Güth, W., Gneezy, U., and Sonsino, D. (2001). On the interaction of risk and time preferences: An experimental study. *German Economic Review*, 2(3):239–253.

Andersen, S., Harrison, G., Lau, M., and Rutstrom, E. (2014). *European Economic Review*, 71:15–33.

Anderson, J. E., Govada, M., Steffen, T. K., Thorne, C. P., Varvarigou, V., Kales, S. N., and Burks, S. V. (2012). Obesity is associated with the future risk of heavy truck crashes among newly recruited commercial drivers. *Accident Analysis & Prevention*, 49:378–384.

Anderson, L. R. and Mellor, J. M. (2008). Predicting health behaviors with an experimental measure of risk preference. *Journal of health economics*, 27(5):1260–1274.

Andreoni, J. and Sprenger, C. (2011). Uncertainty equivalents: Testing the limits of the independence axiom. Technical report, National Bureau of Economic Research.

Anger, S. and Schnitzlein, D. D. (2017). Cognitive skills, non-cognitive skills, and family background: evidence from sibling correlations. *Journal of Population Economics*, 30(2):591–620.

Apicella, C., Dreber, A., Campbell, B., Gray, P., Hoffman, M., and Little, A. (2008). Testosterone and financial risk preferences. *Evolution and human behavior*, 29(6):384–390.

Appelman, Y., van Rijn, B. B., Monique, E., Boersma, E., and Peters, S. A. (2015). Sex differences in cardiovascular risk factors and disease prevention. *Atherosclerosis*, 241:211–218.

Arcaya, M., Glymour, M. M., Christakis, N. A., Kawachi, I., and Subramanian, S. (2014). Individual and spousal unemployment as predictors of smoking and drinking behavior. *Social Science & Medicine*, 110:89–95.

Archer, J. (2006). Testosterone and human aggression: an evaluation of the challenge hypothesis. *Neuroscience & Biobehavioral Reviews*, 30(3):319–345.

Arendt, J. N. (2005). Does education cause better health? a panel data analysis using school reforms for identification. *Economics of Education review*, 24(2):149–160.

Augurzky, B. and Kluve, J. (2007). Assessing the performance of matching algorithms when selection into treatment is strong. *Journal of Applied Econometrics*, 22(3):533–557.

Axon, R. N., Bradford, W. D., and Egan, B. M. (2009). The role of individual time preferences in health behaviors among hypertensive adults: a pilot study. *Journal of the American Society of Hypertension*, 3(1):35–41.

Aycinena, D. and Rentschler, L. (2018). Discounting and digit ratio: Low 2d: 4d predicts patience for a sample of females. *Frontiers in behavioral neuroscience*, 11(257).

Baji, P. and Biro, A. (2018). Adaptation or recovery after health shocks? evidence using subjective and objective health measures. *Health economics*, 27(5):850–864.

Bala, V. and Goyal, S. (1998). Learning from neighbours. *The review of economic studies*, 65(3):595–621.

Balia, S. and Jones, A. M. (2008). Mortality, lifestyle and socio-economic status. *Journal of health economics*, 27(1):1–26.

Barsky, R. B., Juster, F. T., Kimball, M. S., and Shapiro, M. D. (1997). Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *The Quarterly Journal of Economics*, 112(2):537–579.

Bauer, J. and Groneberg, D. A. (2016). Measuring spatial accessibility of health care providers–introduction of a variable distance decay function within the floating catchment area (fca) method. *PloS one*, 11(7):e0159148.

Bauer, J. J. and Bonanno, G. A. (2001). I can, i do, i am: The narrative differentiation of self-efficacy and other self-evaluations while adapting to bereavement. *Journal of research in personality*, 35(4):424–448.

Beaud, M. and Willinger, M. (2016). Quels déterminants de la prise de risque? les réponses de l'économie expérimentale. *L'Actualité économique*, 92(1-2):49–79.

Bechara, A. (2005). Decision making, impulse control and loss of willpower to resist drugs: a neurocognitive perspective. *Nature neuroscience*, 8(11):1458.

Becker, A., Deckers, T., Dohmen, T., Falk, A., and Kosse, F. (2012). The relationship between economic preferences and psychological personality measures. *Annu. Rev. Econ.*, 4(1):453–478.

Bellante, D. and Green, C. A. (2004). Relative risk aversion among the elderly. *Review of Financial Economics*, 13(3):269–281.

Bénassy-Quéré, A., Blanchard, O. J., and Tirole, J. (2017). Les économistes dans la cité. *Notes du conseil danalyse economique*, (6):1–12.

Bibby, P. A. and Ferguson, E. (2011). The ability to process emotional information predicts loss aversion. *Personality and Individual Differences*, 51(3):263–266.

Binswanger, H. P. (1980). Attitudes toward risk: Experimental measurement in rural india. *American journal of agricultural economics*, 62(3):395–407.

Binswanger, H. P. et al. (1981). Attitudes toward risk: Theoretical implications of an experiment in rural india. *Economic Journal*, 91(364):867–890.

Blais, A. and Weber, E. (2006). A domain-specific risk-taking (dospert) scale for adult populations. *Judgment and Decision Making*, 1(1).

Blanco, C., Ibáñez, A., Blanco-Jerez, C.-R., Baca-Garcia, E., and Sáiz-Ruiz, J. (2001). Plasma testosterone and pathological gambling. *Psychiatry research*, 105(1-2):117–121.

Blondel, S., Loheac, Y., and Rinaudo, S. (2007). Rationality and drug use: An experimental approach. *Journal of health economics*, 26(3):643–658.

Bonin, H., Dohmen, T., Falk, A., Huffman, D., and Sunde, U. (2007). Cross-sectional earnings risk and occupational sorting: The role of risk attitudes. *Labour Economics*, 14(6):926–937.

Borghans, L., Duckworth, A. L., Heckman, J. J., and Ter Weel, B. (2008). The economics and psychology of personality traits. *Journal of human Resources*, 43(4):972–1059.

Boyce, C. J., Wood, A. M., and Powdthavee, N. (2013). Is personality fixed? personality changes as much as "variable" economic factors and more strongly predicts changes to life satisfaction. *Social indicators research*, 111(1):287–305.

Brañas Garza, P. and Rustichini, A. (2011). Organizing effects of testosterone and economic behavior: not just risk taking. *PloS one*, 6(12).

Bradford, D. E., Curtin, J. J., and Piper, M. E. (2015). Anticipation of smoking sufficiently dampens stress reactivity in nicotine deprived smokers. *Journal of abnormal psychology*, 124(1).

Bradley, C. J., Neumark, D., and Barkowski, S. (2013). Does employer-provided health insurance constrain labor supply adjustments to health shocks? new evidence on women diagnosed with breast cancer. *Journal of health economics*, 32(5):833–849.

Brañas-Garza, P., Galizzi, M. M., and Nieboer, J. (2018). Experimental and self-reported measures of risk taking and digit ratio (2d: 4d): Evidence from a large, systematic study. *International Economic Review*, 59(3):1131–1157.

Brandt, S., . D. B. (2013). Time and risk preferences and the use of asthma controller medication. *Pediatrics*, 131(4):e1204–e1210.

Broockman, D. and Kalla, J. (2016). Durably reducing transphobia: A field experiment on door-to-door canvassing. *Science*, pages 220–224.

Brown, H. and van der Pol, M. (2014). The role of time preferences in the intergenerational transfer of smoking. *Health economics*, 23(12):1493–1501.

Brown, S. and Taylor, K. (2014). Household finances and the 'big five'personality traits. *Journal of Economic Psychology*, 45:197–212.

Bryson, A., Dorsett, R., and Purdon, S. (2002). The use of propensity score matching in the evaluation of active labour market policies. LSE Research Online Documents on Economics 4993, London School of Economics and Political Science, LSE Library.

Buddelmeyer, H. and Powdthavee, N. (2016). Can having internal locus of control insure against negative shocks? psychological evidence from panel data. *Journal of economic behavior & organization*, 122:88–109.

Budria, S., Diaz-Serrano, L., Ferrer i Carbonell, A., and Hartog, J. (2013). Risk attitude and wage growth: replicating shaw (1996). *Empirical Economics*, 44(2):981–1004.

Bunn, H., Lange, I., Urrutia, M., Sylvia Campos, M., Campos, S., Jaimovich, S., Campos, C., Jacobsen, M. J., and Gaboury, I. (2006). Health preferences and decision-making needs of disadvantaged women. *Journal of advanced nursing*, 56(3):247–260.

Burke, M. A. and Heiland, F. (2007). Social dynamics of obesity. *Economic Inquiry*, 45(3):571–591.

Burks, S. V., Carpenter, J. P., Goette, L., and Rustichini, A. (2009). Cognitive skills affect economic preferences, strategic behavior, and job attachment. *Proceedings of the National Academy of Sciences*, 106(19):7745–7750.

Burns, D. M. (2000). Cigarette smoking among the elderly: disease consequences and the benefits of cessation. *American Journal of Health Promotion*, 14(6):357–361.

Byrnes, J. P., Miller, D. C., and Schafer, W. D. (1999). Gender differences in risk taking: A meta-analysis.

Cai, L., Mavromaras, K., and Oguzoglu, U. (2014). The effects of health status and health shocks on hours worked. *Health economics*, 23(5):516–528.

Calhoun, L. G., Cann, A., Tedeschi, R. G., and McMillan, J. (2000). A correlational test of the relationship between posttraumatic growth, religion, and cognitive processing. *Journal of Traumatic Stress: Official Publication of The International Society for Traumatic Stress Studies*, 13(3):521–527.

Caliendo, M., Cobb-Clark, D. A., and Uhlendorff, A. (2010). Locus of control and job search strategies.

Caliendo, M. and Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of economic surveys*, 22(1):31–72.

Campbell, W. K. and Sedikides, C. (1999). Self-threat magnifies the self-serving bias: A meta-analytic integration. *Review of general Psychology*, 3(1):23.

Canli, T. (2006). *Biology of personality and individual differences*. Guilford Press.

Cebi, M. (2007). Locus of control and human capital investment revisited. *Journal of Human Resources*, 42(4):919–932.

Chabris, C. F., Laibson, D., Morris, C. L., Schuldt, J. P., and Taubinsky, D. (2008). Individual laboratory measured discount rates predict field behavior. *Journal of risk and uncertainty*, 37:2.

Chaloupka, F. (1991). Rational addictive behavior and cigarette smoking. *Journal of political Economy*, 99(4):722–742.

Chaloupka, F. J. and Wechsler, H. (1997). Price, tobacco control policies and smoking among young adults. *Journal of health economics*, 16(3):359–373.

Chandra, A., Gruber, J., and McKnight, R. (2010). Patient cost-sharing and hospitalization offsets in the elderly. *American Economic Review*, 100(1):193–213.

Chapman, G. B. and Coups, E. J. (1999). Predictors of influenza vaccine acceptance among healthy adults. *Preventive medicine*, 29(4):249–262.

Charness, G. and Viceisza, A. (2015). Three risk-elicitation methods in the field: Evidence from rural senegal.

Cheng, T. C., L. J. . V. R. (2019). Monthly spending dynamics of the elderly following a health shock: Evidence from singapore. *Health economics*, 28(1):23–43.

Chiappori, P. A. and Paiella, M. (2011). Relative risk aversion is constant: Evidence from panel data. *Journal of the European Economic Association*, 9(6):1021–1052.

Chiteji, N. (2010). Time preference, noncognitive skills and well being across the life course: do noncognitive skills encourage healthy behavior? *American Economic Review*, 100(2):200–204.

Christensen, A. J. and Johnson, J. A. (2002). Patient adherence with medical treatment regimens: An interactive approach. *Current directions in psychological science*, 11(3):94–97.

Chuang, Y. and Schechter, L. (2015). Stability of experimental and survey measures of risk, time, and social preferences: A review and some new results. *Journal of Development Economics*, 117:151–170.

Clark, A. and Etilé, F. (2002). Do health changes affect smoking? evidence from british panel data. *Journal of health economics*, 21(4):533–562.

Clark, A. E. and Etile, F. (2006). Don't give up on me baby: Spousal correlation in smoking behaviour. *Journal of Health Economics*, 25(5):958 – 978.

Clark, A. E. and Lelkes (2005). Deliver us from evil: Religion as insurance.

Cobb-Clark, D. A., Kassenboehmer, S. C., and Schurer, S. (2014). Healthy habits: The connection between diet, exercise, and locus of control. *Journal of Economic Behavior & Organization*, 98:1–28.

Cobb-Clark, D. A., Kassenboehmer, S. C., and Sinning, M. G. (2016). Locus of control and savings. *Journal of Banking & Finance*, 73:113–130.

Cobb-Clark, D. A. and Schurer, S. (2012). The stability of big-five personality traits. *Economics Letters*, 115(1):11–15.

Cobb-Clark, D. A. and Schurer, S. (2013). Two economists' musings on the stability of locus of control. *The Economic Journal*, 123(570).

Cobb-Clark, D. A. and Tan, M. (2011). Noncognitive skills, occupational attainment, and relative wages. *Labour Economics*, 18(1):1–13.

Coile, C. and Milligan, K. (2009). How household portfolios evolve after retirement: The effect of aging and health shocks. *Review of Income and Wealth*, 55(2):226–248.

Coleman, M. and DeLeire, T. (2003). An economic model of locus of control and the human capital investment decision. *Journal of Human Resources*, 38(3):701–721.

Coller, M. and Williams, M. B. (1999). Eliciting individual discount rates. *Experimental Economics*, 2(2):107–127.

Conell-Price, L. and Jamison, J. (2015). Predicting health behaviors with economic preferences & locus of control. *Journal of Behavioral and Experimental Economics*, 54:1–9.

Conley, D. and Thompson, J. (2013). The effects of health and wealth shocks on retirement decisions. *Federal Reserve Bank of St. Louis Review*, 95(5):389–404.

Conti, G., Heckman, J., and Urzua, S. (2010). The education-health gradient. *American Economic Review*, 100(2):234–38.

Contoyannis, P. and Jones, A. M. (2004). Socio-economic status, health and lifestyle. *Journal of health economics*, 23(5):965–995.

Costa, P. T. and McCrae, R. R. (1992a). Four ways five factors are basic. *Personality and individual differences*, 13(6):653–665.

Costa, P. T. and McCrae, R. R. (1992b). Normal personality assessment in clinical practice: The neo personality inventory. *Psychological assessment*, 4(1):5.

Craig, B. M., Reeve, B. B., Cella, D., Hays, R. D., Pickard, A. S., and Revicki, D. A. (2014). Demographic differences in health preferences in the united states. *Medical care*, 52(4):307.

Crainich, D., Eeckhoudt, L., and Flambard, V. (2014). Préférence face au risque et difficultés financières des ménages les plus pauvres. *Economie et statistique*, 472(1):195–211.

Cramer, J. S., Hartog, J., Jonker, N., and Van Praag, C. M. (2002). Low risk aversion encourages the choice for entrepreneurship: an empirical test of a truism. *Journal of economic behavior and organization*, 48(1):29–36.

Crosetto, P. and Filippin, A. (2016). A theoretical and experimental appraisal of four risk elicitation methods. *Experimental Economics*, 19(3):613–641.

Croson, R. and Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic literature*, 47(2):448–74.

Cunha, F., Heckman, J. J., and Schennach, S. M. (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrica*, 78(3):883–931.

Currie, J. (2009). Healthy, wealthy, and wise: Socioeconomic status, poor health in childhood, and human capital development. *JoUrnal of economIc lIteratUre*, 47(1):87–122.

Cutler, D. M. and Lleras-Muney, A. (2010). Understanding differences in health behaviors by education. *Journal of health economics*, 29(1):1–28.

Dabbs Jr, J. M. and Morris, R. (1990). Testosterone, social class, and antisocial behavior in a sample of 4,462 men. *Psychological Science*, 1(3):209–211.

Dafny, L., Duggan, M., and Ramanarayanan, S. (2012). Paying a premium on your premium? consolidation in the us health insurance industry. *American Economic Review*, 102(2):1161–85.

Daly, M., Harmon, C. P., and Delaney, L. (2009). Psychological and biological foundations of time preference. *Journal of the European Economic Association*, 7(2):659–669.

Damasio, H., Grabowski, T., Frank, R., Galaburda, A. M., and Damasio, A. R. (2005). *The return of Phineas Gage: Clues about the brain from the skull of a famous patient.* New York, NY, US, Psychology Press.

Darden, M., Gilleskie, D. B., and Strumpf, K. (2018). Smoking and mortality: New evidence from a long panel. *International Economic Review*, 59(3):1571–1619.

de Chaisemartin, C. and D'Haultfœuille, X. (2016). Double fixed effects estimators with heterogeneous treatment effects. Technical report, Working paper.

De Chaisemartin, C., Geoffard, P.-Y., and le Faou, A.-L. (2011). Workplace smoking ban effects on unhappy smokers. *Health economics*, 20(9):1043–1055.

Decker, S. and Schmitz, H. (2016). Health shocks and risk aversion. *Journal of health economics*, 50:156–170.

Dehejia, R. H. and Wahba, S. (2002). Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and statistics*, 84(1):151–161.

Dercon, S., Hoddinott, J., Woldehanna, T., et al. (2005). Shocks and consumption in 15 ethiopian villages, 1999-2004. *Journal of African economies*, 14(4):559.

DeYoung, C. G., Hirsh, J. B., Shane, M. S., Papademetris, X., Rajeevan, N., and Gray, J. R. (2010). Testing predictions from personality neuroscience: Brain structure and the big five. *Psychological science*, 21(6):820–828.

Diamond, A. and Sekhon, J. S. (2013). Genetic matching for estimating causal effects: A general multivariate matching method for achieving balance in observational studies. *Review of Economics and Statistics*, 95(3):932–945.

Digman, J. M. (1990). Personality structure: Emergence of the five-factor model. *Annual review of psychology*, 41(1):417–440.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., and Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association*, 9(3):522–550.

Dohmen, T. J., Falk, A., Huffman, D., Sunde, U., Schupp, J., and Wagner, G. G. (2005). Individual risk attitudes: New evidence from a large, representative, experimentally-validated survey.

Dolor, R. J., Østbye, T., Lyna, P., Coffman, C. J., Alexander, S. C., Tulsky, J. A., Brouwer, R. J. N., Esoimeme, I., and Pollak, K. I. (2010). What are physicians' and patients' beliefs about diet, weight, exercise, and smoking cessation counseling? *Preventive medicine*, 51(5):440.

Doyle Jr, J. J. (2005). Health insurance, treatment and outcomes: using auto accidents as health shocks. *Review of Economics and Statistics*, 87(2):256–270.

Dreber, A. and Hoffman, M. (2007). Risk preferences are partly predetermined. *Mimeo, Stockholm School of Economics*.

Drichoutis, A. and Nayga Jr, R. (2015). Do risk and time preferences have biological roots? *Southern Economic Journal*, 82(1):235–256.

Duesenberry, J. S. et al. (1949). Income, saving, and the theory of consumer behavior.

Duggan, M. and Scott Morton, F. (2010). The effect of medicare part d on pharmaceutical prices and utilization. *American Economic Review*, 100(1):590–607.

Dupilet, C., Grignon, M., and Pierrard, B. (2002). *Modèles économiques et politiques de lutte contre le tabagisme*. CREDES.

Dyer, J. S. and Sarin, R. K. (1982). Relative risk aversion. *Management Science*, 28(8):875–886.

Eckel, C. and Grossman, P. (2008a). Differences in the economic decisions of men and women: Experimental evidence. *Handbook of experimental economics results*, 1:509–519.

Eckel, C. C. and Grossman, P. J. (1996). Altruism in anonymous dictator games. *Games and economic behavior*, 16(2):181–191.

Eckel, C. C. and Grossman, P. J. (2002). Sex differences and statistical stereotyping in attitudes toward financial risk. *Evolution and human behavior*, 23(4):281–295.

Eckel, C. C. and Grossman, P. J. (2008b). Men, women and risk aversion: Experimental evidence. *Handbook of experimental economics results*, 1:1061–1073.

Edwards, A., Elwyn, G., Covey, J., Matthews, E., and Pill, R. (2001). Presenting risk information a review of the effects of framing and other manipulations on patient outcomes. *Journal of health communication*, 6(1):61–82.

Eisenberg, D., Golberstein, E., and Whitlock, J. L. (2014). Peer effects on risky behaviors: New evidence from college roommate assignments. *Journal of Health Economics*, 33:126 – 138.

Ekelund, J., Johansson, E., Jarvelin, M. R., and Lichtermann, D. (2005). Self-employment and risk aversion—evidence from psychological test data. *Labour Economics*, 12(5):649–659.

Elkins, R. K., Kassenboehmer, S. C., and Schurer, S. (2017). The stability of personality traits in adolescence and young adulthood. *Journal of Economic Psychology*, 60:37–52.

Etilé, F. (2004). Politiques publiques des drogues et modèles de dépendance. *Revue économique*, 55(4):715–744.

Etilé, F. (2007). Social norms, ideal body weight and food attitudes. *Health Economics*, 16(9):945–966.

Falba, T. (2005). Health events and the smoking cessation of middle aged americans. *Journal of behavioral medicine*, 28(1):21–33.

Falk, A. and Fischbacher, U. (2006). A theory of reciprocity. *Games and economic behavior*, 54(2):293–315.

Fan, E. and Zhao, R. (2009). Health status and portfolio choice: Causality or heterogeneity? *Journal of Banking & Finance*, 33(6):1079–1088.

Fang, H. and Gavazza, A. (2011). Dynamic inefficiencies in an employment-based health insurance system: Theory and evidence. *American Economic Review*, 101(7):3047–77.

Feinberg, R. M. (1977). Risk aversion, risk, and the duration of unemployment. *The Review of Economics and Statistics*, pages 264–271.

Feinstein, L. (2000). *The relative economic importance of academic, psychological and behavioural attributes developed on childhood*. Centre for Economic Performance, London School of Economics and Political ....

Figner, B., Knoch, D., Johnson, E. J., Krosch, A. R., Lisanby, S. H., Fehr, E., and Weber, E. U. (2010). Lateral prefrontal cortex and self-control in intertemporal choice. *Nature neuroscience*, 13(5):538.

Filippin, A. and Crosetto, P. (2016). A reconsideration of gender differences in risk attitudes. *Management Science*, 62(11):3138–3160.

Flouri, E. (2006). Parental interest in children's education, children's self-esteem and locus of control, and later educational attainment: Twenty-six year follow-up of the 1970 british birth cohort. *British journal of Educational psychology*, 76(1):41–55.

Fossen, F. M. and Glocker, D. (2017). Stated and revealed heterogeneous risk preferences in educational choice. *European Economic Review*, 97(5):1–25.

Frederick, S. and Loewenstein, G., . O. d. T. (2002). Time discounting and time preference: A critical review. *Journal of economic literature*, 40(2):351–401.

Friedman, M. (1953). *Essays in positive economics*. University of Chicago Press.

Fuchs-Schundeln, N., . S. M. (2005). Precautionary savings and self-selection: Evidence from the german reunification experiment. *The Quarterly Journal of Economics*, 120(3):1085–1120.

Galatzer-Levy, I. R. and Bonanno, G. A. (2013). Heterogeneous patterns of stress over the four years of college: Associations with anxious attachment and ego-resiliency. *Journal of personality*, 81(5):476–486.

Galizzi, M. M., Machado, S. R., and Miniaci, R. (2016a). Temporal stability, cross-validity, and external validity of risk preferences measures: experimental evidence from a uk representative sample. *Cross-Validity, and External Validity of Risk Preferences Measures: Experimental Evidence from a UK Representative Sample (August 12, 2016).*

Galizzi, M. M. and Miraldo, M. (2017). Are you what you eat? healthy behaviour and risk preferences. *The BE Journal of Economic Analysis & Policy*, 17(1).

Galizzi, M. M., Miraldo, M., and Stavropoulou, C. (2016b). In sickness but not in wealth: field evidence on patients' risk preferences in financial and health domains. *Medical Decision Making*, 36(4):503–517.

Garbarino, E., Slonim, R., and Sydnor, J. (2011). Digit ratios (2d:4d) as predictors of risky decision making for both sexes. *Journal of Risk and Uncertainty*, 42:1–26.

Garcia-Gomez, P. (2011). Institutions, health shocks and labour market outcomes across europe. *Journal of health economics*, 30(1):200–213.

Garcia Gomez, P. and Lopez Nicola, A. (2006). Health shocks, employment and income in the spanish labour market. *Health economics*, 15(9):997–1009.

Garcia-Gomez, P., Van Kippersluis, H., O'Donnell, O., and Van Doorslaer, E. (2013). Long-term and spillover effects of health shocks on employment and income. *Journal of Human Resources*, 48(4):873–909.

Garrido, M. M., Kelley, A. S., Paris, J., Roza, K., Meier, D. E., Morrison, R. S., and Aldridge, M. D. (2014). Methods for constructing and assessing propensity scores. *Health services research*, 49(5):1701–1720.

Gloede, O., Menkhoff, L., and Waibel, H. (2015). Shocks, individual risk attitude, and vulnerability to poverty among rural households in thailand and vietnam. *World Development*, 71:54–78.

Godtfredsen, N. S., Prescott, E., Osler, M., and Vestbo, J. (2001). Predictors of smoking reduction and cessation in a cohort of danish moderate and heavy smokers. *Preventive medicine*, 33(1):46–52.

Goldberg, L. R. (1992). The development of markers for the big-five factor structure. *Psychological assessment*, 4(1).

Goldberg, M., Leclerc, A., Bonenfant, S., Chastang, J. F., Schmaus, A., Kaniewski, N., and Zins, M. (2006). Cohort profile: the gazel cohort study. *International journal of epidemiology*, 36(1):32–39.

Gollier, C. (2001). The economics of risk and time. *The MIT Press*.

Gollier, C. (2008). Intergenerational risk-sharing and risk-taking of a pension fund. *Journal of Public Economics*, 92(5-6):1463–1485.

Graham, L. and Oswald, A. J. (2010). Hedonic capital, adaptation and resilience. *Journal of Economic Behavior & Organization*, 76(2):372–384.

Gray, M. J., Litz, B. T., Hsu, J. L., and Lombardo, T. W. (2004). Psychometric properties of the life events checklist. *Assessment*, 11(4):330–341.

Greiner, G. G., Schwettmann, L., Goebel, J., and Maier, W. (2018). Primary care in germany: access and utilisation—a cross-sectional study with data from the german socio-economic panel (soep). *BMJ open*, 8(10):e021036.

Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political economy*, 80(2):223–255.

Groves, M. O. (2005). How important is your personality? labor market returns to personality for women in the us and uk. *Journal of Economic Psychology*, 26(6):827–841.

Guiso, L., . P. M. (2004). The role of risk aversion in predicting individual behaviors. *Unpublished paper*.

Hagan, R., J. A. . R. N. (2009). Health and retirement in europe. *International Journal of Environmental Research and Public Health*, 6(10):2676–2695.

Hainmueller, J. and Xu, Y. (2013). Ebalance: A stata package for entropy balancing. *Journal of Statistical Software*, 54(7).

Hammitt, J. K. and Haninger, K. (2010). Valuing fatal risks to children and adults: Effects of disease, latency, and risk aversion. *Journal of Risk and Uncertainty*, 40(1):57–83.

Hampson, S. E., Goldberg, L. R., Vogt, T. M., and Dubanoski, J. P. (2007). Mechanisms by which childhood personality traits influence adult health status: educational attainment and healthy behaviors. *Health psychology*, 26(1):121.

Hampson, S. E., Tildesley, E., Andrews, J. A., Luyckx, K., and Mroczek, D. K. (2010). The relation of change in hostility and sociability during childhood to substance use in mid adolescence. *Journal of Research in Personality*, 44(1):103–114.

Hanaoka, C., Shigeoka, H., and Watanabe, Y. (2018). Do risk preferences change? evidence from the great east japan earthquake. *American Economic Journal: Applied Economics*, 10(2):298–330.

Harbaugh, W. T., Krause, K., and Vesterlund, L. (2002). Risk attitudes of children and adults: Choices over small and large probability gains and losses. *Experimental Economics*, 5(1):53–84.

Harris, J. E., Balsa, A. I., and Triunfo, P. (2015). Tobacco control campaign in uruguay: Impact on smoking cessation during pregnancy and birth weight. *Journal of health economics*, 42:186–196.

Harrison, G. W., Hofmeyr, A., Ross, D., and Swarthout, J. T. (2015). Risk preferences, time preferences and smoking behaviour. In *Third Workshop on Behavioural and Experimental Health Economics*.

Harrison, G. W., Lau, M. I., and Williams, M. B. (2002). Estimating individual discount rates in denmark: A field experiment. *American economic review*, 92(5):1606–1617.

Harrison, G. W. and Rutstrom, E. E. (2009). Expected utility theory and prospect theory: One wedding and a decent funeral. *Experimental Economics*, 12(2):133.

Hartog, J., Ferrer i Carbonell, A., and Jonker, N. (2002). Linking measured risk aversion to individual characteristics. *Kyklos*, 55(1):3–26.

Heckman, J. J., Ichimura, H., and Todd, P. (1998). Matching as an econometric evaluation estimator. *The review of economic studies*, 65(2):261–294.

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The review of economic studies*, 64(4):605–654.

Heckman, J. J. and Kautz, T. (2012). Hard evidence on soft skills. *Labour economics*, 19(4):451–464.

Heckman, J. J., Stixrud, J., and Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor economics*, 24(3):411–482.

Heider, F. (2013). *The psychology of interpersonal relations*. Psychology Press.

Heineck, G. and Anger, S. (2010). The returns to cognitive abilities and personality traits in germany. *Labour economics*, 17(3):535–546.

Helgeson, V. S., Reynolds, K. A., and Tomich, P. L. (2006). A meta-analytic review of benefit finding and growth. *Journal of consulting and clinical psychology*, 74(5):797.

Herd, N., Borland, R., and Hyland, A. (2009). Predictors of smoking relapse by duration of abstinence: findings from the international tobacco control (itc) four country survey. *Addiction*, 104(12):2088–2099.

Hermans, E. J., Putman, P., and Van Honk, J. (2006). Testosterone administration reduces empathetic behavior: A facial mimicry study. *Psychoneuroendocrinology*, 31(7):859–866.

Hertwig, R., Barron, G., Weber, E. U., and Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological science*, 15(8):534–539.

Hey, J. D. and Orme, C. (1994). Investigating generalizations of expected utility theory using experimental data. *Econometrica: Journal of the Econometric Society*, pages 1291–132.

Hirsh, J. B. and Inzlicht, M. (2008). The devil you know: Neuroticism predicts neural response to uncertainty. *Psychological science*, 19(10):962–967.

Ho, D. E., Imai, K., King, G., and Stuart, E. A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political analysis*, 15(3):199–236.

Hoerger, M., Chapman, B. P., Prigerson, H. G., Fagerlin, A., Mohile, S. G., Epstein, R. M., Lyness, J. M., and Duberstein, P. R. (2014). Personality change pre-to post-loss in spousal caregivers of patients with terminal lung cancer. *Social psychological and personality science*, 5(6):722–729.

Hofstede, G. (1991). Cultures and organizations. intercultural cooperation and its importance for survival. software of the mind. *London: Mc Iraw-Hill*.

Hogan, J., Barrett, P., and Hogan, R. (2007). Personality measurement, faking, and employment selection. *Journal of Applied Psychology*, 92(5):1270.

Holt, C. A. and Laury, S. K. (2002). Risk aversion and incentive effects. *American economic review*, 92(5):1644–1655.

Hotz, V. J. and Xiao, M. (2011). The impact of regulations on the supply and quality of care in child care markets. *American Economic Review*, 101(5):1775–1805.

Hoyt, G. M. and Chaloupka, F. J. (1994). Effect of survey conditions on self-reported substance use. *Contemporary Economic Policy*, 12(3):109–121.

Hryshko, D., Luengo Prado, M. J., and Sorensen, B. E. (2016). Childhood determinants of risk aversion: The long shadow of compulsory education. *Quantitative Economics*, 2(1):37–72.

Hsieh, C.-R. (1998). Health risk and the decision to quit smoking. *Applied economics*, 30(6):795–804.

Hughes, J. R., Keely, J., and Naud, S. (2004). Shape of the relapse curve and long-term abstinence among untreated smokers. *Addiction*, 99(1):29–38.

Imai, K. and Ratkovic, M. (2014). Covariate balancing propensity score. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 76(1):243–263.

Imbens, G. W. and Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of economic literature*, 47(1):5–86.

Jackle, A., Kelsey, B., Burton, J., and Couper, M. P. (2018). Understanding data linkage consent in longitudinal surveys.

Jackle, A., Lynn, P., and Burton, J. (2013). Going online with a face-to-face household panel: initial results from an experiment on the understanding society innovation panel. *Institute for Social and Economic Research, University of Essex*.

Jayawickreme, E. and Blackie, L. E. (2014). Post-traumatic growth as positive personality change: Evidence, controversies and future directions. *European Journal of Personality*, 28(4):312–331.

John, O. P. (1990). The big five factor taxonomy: Dimensions of personality in the natural language and in questionnaires. *Handbook of personality: Theory and research*.

John, O. P. and Srivastava, S. (1999). The big five trait taxonomy: History, measurement, and theoretical perspectives. *Handbook of personality: Theory and research*, 2:102–138.

Jones, A. M. (1989). A double-hurdle model of cigarette consumption. *Journal of applied econometrics*, 4(1):23–39.

Jones, A. M. (1994). Health, addiction, social interaction and the decision to quit smoking. *Journal of health economics*, 13(1):93–110.

Jones, A. M., Laporte, A., Rice, N., and Zucchelli, E. (2015). Do public smoking bans have an impact on active smoking? evidence from the uk. *Health economics*, 24(2):175–192.

Jones, A. M., Rice, N., Robone, S., et al. (2018). The effect of health shocks on financial risk preferences differs by personality traits. Technical report, HEDG, c/o Department of Economics, University of York.

Jones, A. M., Rice, N., and Zantomio, F. (2016). Acute health shocks and labour market outcomes.

Jusot, F., Khlat, M., Rochereau, T., and Serme, C. (2008). Job loss from poor health, smoking and obesity: a national prospective survey in france. *Journal of Epidemiology & Community Health*, 62(4):332–337.

Kandel, D. B., Griesler, P. C., and Schaffran, C. (2009). Educational attainment and smoking among women: risk factors and consequences for offspring. *Drug and alcohol dependence*, 104:S24–S33.

Kautz, T., Heckman, J. J., Diris, R., Ter Weel, B., and Borghans, L. (2014). Fostering and measuring skills: Improving cognitive and non-cognitive skills to promote lifetime success. Technical report, National Bureau of Economic Research.

Keenan, P. S. (2009). Smoking and weight change after new health diagnoses in older adults. *Archives of Internal Medicine*, 169(3):237–242.

Kelly, M. M., Jensen, K. P., and Sofuoglu, M. (2015). Co-occurring tobacco use and posttraumatic stress disorder: Smoking cessation treatment implications. *The American journal on addictions*, 24(8):695–704.

Khwaja, A., Sloan, F., and Chung, S. (2006). The effects of spousal health on the decision to smoke: Evidence on consumption externalities, altruism and learning within the household. *Journal of Risk and Uncertainty*, 32(1):17–35.

Kirby, K. N., . P. N. M. (2004). Heroin and cocaine abusers have higher discount rates for delayed rewards than alcoholics or non drug using controls. *Addiction*, 99(4):461–471.

Kirby, K. N., Petry, N. M., and Bickel, W. K. (1999). Heroin addicts have higher discount rates for delayed rewards than non-drug-using controls. *Journal of Experimental psychology: general*, 128(1).

Knickmeyer, R., Baron-Cohen, S., Raggatt, P., Taylor, K., and Hackett, G. (2006). Fetal testosterone and empathy. *Hormones and Behavior*, 49(3):282–292.

Kokot, J. (2017). Does a spouse's health shock influence the partner's risk attitudes? Technical report, Ruhr Economic Papers.

Komlos, J., Smith, P. K., and Bogin, B. (2004). Obesity and the rate of time preference: is there a connection? *Journal of biosocial science*, 36(2):209–219.

Kong, G., Cavallo, D. A., Camenga, D. R., Morean, M. E., and Krishnan-Sarin, S. (2016). Preference for gain-or loss-framed electronic cigarette prevention messages. *Addictive behaviors*, 62:108–113.

Kopp, P. and Fenoglio, P. (2011). Les drogues sont-elles bénéfiques pour la france? *Revue économique*, 62(5):899–918.

Kosfeld, M., Heinrichs, M., Zak, P. J., Fischbacher, U., and Fehr, E. (2005). Oxytocin increases trust in humans. *Nature*, 435(7042):673.

Kotz, D., Fidler, J., and West, R. (2012). Very low rate and light smokers: smoking patterns and cessation-related behaviour in england, 2006–11. *Addiction*, 107(5):995–1002.

Kotz, D., Willemsen, M. C., Brown, J., and West, R. (2013). Light smokers are less likely to receive advice to quit from their gp than moderate-to-heavy smokers: a comparison of national survey data from the netherlands and england. *The European journal of general practice*, 19(2):99–105.

Koudstaal, M., Sloof, R., and Van Praag, M. (2015). Risk, uncertainty, and entrepreneurship: Evidence from a lab-in-the-field experiment. *Management Science*, 62(10):2897–2915.

Kreuter, M. W. and Holt, C. L. (2001). How do people process health information? applications in an age of individualized communication. *Current Directions in Psychological Science*, 10(6):206–209.

Kreuter, M. W. and Skinner, C. S. (2000). Tailoring: what's in a name?

Krupp, H.-J. (2008). The german socio-economic panel: How it all began.

Kuhn, P. and Weinberger, C. (2005). Leadership skills and wages. *Journal of Labor Economics*, 23(3):395–436.

Laporte, A., Dass, A. R., and Ferguson, B. S. (2016). Is the rational addiction model inherently impossible to estimate? *Journal of Health Economics*.

Laporte, A. and Windmeijer, F. (2005). Estimation of panel data models with binary indicators when treatment effects are not constant over time. *Economics Letters*, 88(3):389–396.

Lawless, L., Drichoutis, A. C., and Nayga, R. M. (2013). Time preferences and health behaviour: a review. *Agricultural and Food Economics*, 1(1).

Lechner, M. (2002). Program heterogeneity and propensity score matching: An application to the evaluation of active labor market policies. *Review of Economics and Statistics*, 84(2):205–220.

Lechner, M., Miquel, R., and Wunsch, C. (2011). Long-run effects of public sector sponsored training in west germany. *Journal of the European Economic Association*, 9(4):742–784.

Lee, A. J., Crombie, I. K., Smith, W. C., and Tunstall-Pedoe, H. D. (1991). Cigarette smoking and employment status. *Social science & medicine*, 33(11):1309–1312.

Lee, J. and Kim, H. (2008). A longitudinal analysis of the impact of health shocks on the wealth of elders. *Journal of Population Economics*, 21(1):217–230.

Lezak, M. D. (1987). Relationships between personality disorders, social disturbances, and physical disability following traumatic brain injury. *The Journal of head trauma rehabilitation*.

Lindeboom, M., Llena-Nozal, A., and van der Klaauw, B. (2007). Health shocks, disability and work. *Unpublished manuscript, Department of Economics, Free University Amsterdam*.

Linley, P. A. and Joseph, S. (2004). Positive change following trauma and adversity: A review. *Journal of Traumatic Stress: Official Publication of The International Society for Traumatic Stress Studies*, 17(1):11–21.

Liu, J.-T. and Hsieh, C.-R. (1995). Risk perception and smoking behavior: Empirical evidence from taiwan. *Journal of Risk and Uncertainty*, 11(2):139–157.

Loewenstein, G. F., Weber, E. U., Hsee, C. K., and Welch, N. (2001). Risk as feelings. *Psychological bulletin*, 127(2):267.

Loomes, G. and Pogrebna, G. (2014). Measuring individual risk attitudes when preferences are imprecise. *The Economic Journal*, 124(576):569–593.

Loonis, É. (2001). Les modèles économiques des addictions. *Psychotropes*, 7(2):7–22.

Lotterman, J. H., Bonanno, G. A., and Galatzer-Levy, I. (2014). The heterogeneity of long-term grief reactions. *Journal of affective disorders*, 167:12–19.

Love, D. A. and Smith, P. A. (2010). Does health affect portfolio choice? *Health economics*, 19(12):1441–1460.

Lucas, M. and Koff, E. (2010). Delay discounting is associated with the 2d: 4d ratio in women but not men. *Personality and Individual Differences*, 48(2):182–186.

Lundborg, P. and Andersson, H. (2008). Gender, risk perceptions, and smoking behavior. *Journal of Health Economics*, 27(5):1299–1311.

Lundborg, P., Nilsson, M., and Vikstrom, J. (2015). Heterogeneity in the impact of health shocks on labour outcomes: evidence from swedish workers. *Oxford Economic Papers*, 67(3):715–739.

Lusk, J. L. and Coble, K. H. (2005). Risk perceptions, risk preference, and acceptance of risky food. *American Journal of Agricultural Economics*, 87(2):393–405.

Lutchmaya, S., Baron-Cohen, S., Raggatt, P., Knickmeyer, R., and Manning, J. T. (2004). 2nd to 4th digit ratios, fetal testosterone and estradiol. *Early human development*, 77(1-2):23–28.

Manning, J., Kilduff, L., Cook, C., Crewther, B., and Fink, B. (2014). Digit ratio (2d:4d): A biomarker for prenatal sex steroids and adult sex steroids in challenge situations. *Frontiers in endocrinology*, 5:9.

Manning, J. T., Bundred, P. E., and Flanagan, B. F. (2002). The ratio of 2nd to 4th digit length: a proxy for transactivation activity of the androgen receptor gene? *Medical hypotheses*, 59(3):334–6.

Manning, J. T., Scutt, D., Wilson, J., and Lewis-Jones, D. I. (1998). The ratio of 2nd to 4th digit length: a predictor of sperm numbers and concentrations of testosterone, luteinizing hormone and oestrogen. *Human Reproduction (Oxford, England)*, 13(11):3000–3004.

Marshall, T. C., L. K. and Ferenczi, N. (2015). The big five, self-esteem, and narcissism as predictors of the topics people write about in facebook status updates. *Personality and Individual Differences*, 85:35–40.

Masanja, I. M., Lutambi, A. M., and Khatib, R. A. (2012). Do health workers' preferences influence their practices? assessment of providers' attitude and personal use of new treatment recommendations for management of uncomplicated malaria, tanzania. *BMC Public Health*, 12(1):956.

Mataró, M., Jurado, M. Á., García-Sánchez, C., Barraquer, L., Costa-Jussá, F. R., and Junqué, C. (2001). Long-term effects of bilateral frontal brain lesion: 60 years after injury with an iron bar. *Archives of Neurology*, 58(7):1139–1142.

Mazur, A. and Booth, A. (1998). Testosterone and dominance in men. *Behavioral and brain sciences*, 21(3):353–363.

McClellan, M. B. (1998). Health events, health insurance, and labor supply: Evidence from the health and retirement survey. In *Frontiers in the Economics of Aging*, pages 301–350. University of Chicago Press.

McGeary, K. A. (2009). How do health shocks influence retirement decisions? *Review of Economics of the Household*, 7(3):307–321.

McGee, A. and McGee, P. (2016). Search, effort, and locus of control. *Journal of Economic Behavior and Organization*, 126:89–101.

McGee, A. D. (2015). How the perception of control influences unemployed job search. *ILR Review*, 68(1):184–211.

McLaren, L. and Petit, R. (2018). Universal and targeted policy to achieve health equity: a critical analysis of the example of community water fluoridation cessation in calgary, canada in 2011. *Critical Public Health*, 28(2):153–164.

McMillen, J. C., Smith, E. M., and Fisher, R. H. (1997). Perceived benefit and mental health after three types of disaster. *Journal of consulting and clinical psychology*, 65(5):733.

Meier, S., . S. C. (2010). Present-biased preferences and credit card borrowing. *American Economic Journal: Applied Economics*, 2(1):193–210.

Mendolia, S. and Walker, I. (2014). The effect of noncognitive traits on health behaviours in adolescence. *Health economics*, 23(9):1146–1158.

Meyer, C., Rumpf, H.-J., Schumann, A., Hapke, U., and John, U. (2003). Intentionally reduced smoking among untreated general population smokers: prevalence, stability, prediction of smoking behaviour change and differences between subjects choosing either reduction or abstinence. *Addiction*, 98(8):1101–1110.

Meyer, D. J. and Meyer, J. (2005). Relative risk aversion: What do we know? *Journal of Risk and Uncertainty*, 31(3):243–262.

Meyerowitz, B. E. and Chaiken, S. (1987). The effect of message framing on breast self-examination attitudes, intentions, and behavior. *Journal of personality and social psychology*, 52(3):500.

Millet, K. and Dewitte, S. (2008). A subordinate status position increases the present value of financial resources for low 2d: 4d men. *American Journal of Human Biology*, 20(1):110–115.

Mongin, P. (1997). Expected utility theory. *Handbook of economic methodology*, 342350.

Monterosso, J. R. and Luo, S. (2010). An argument against dual valuation system competition: Cognitive capacities supporting future orientation mediate rather than compete with visceral motivations. *Journal of Neuroscience, Psychology, and Economics*, 3(1):1.

Moorman, M. and van den Putte, B. (2008). The influence of message framing, intention to quit smoking, and nicotine dependence on the persuasiveness of smoking cessation messages. *Addictive behaviors*, 33(10):1267–1275.

Mueller, S. L., . T. A. S. (2001). Culture and entrepreneurial potential: A nine country study of locus of control and innovativeness. *Journal of business venturing*, 16(1):51–75.

Nisbett, R. E. and Ross, L. (1980). Human inference: Strategies and shortcomings of social judgment.

Novo, M., Hammarström, A., and Janlert, U. (2000). Smoking habits—a question of trend or unemployment? a comparison of young men and women between boom and recession. *Public Health*, 114(6):460 – 463.

Nuscheler, R., . R. K. (2016). To vaccinate or to procrastinate? that is the prevention question. *Health economics*, 25(12):1560–1581.

O'Keefe, D. J. and Jensen, J. D. (2009). The relative persuasiveness of gain-framed and loss-framed messages for encouraging disease detection behaviors: A meta-analytic review. *Journal of Communication*, 59(2):296–316.

Op den Velde, W., Aarts, P. G., Falger, P. R., Hovens, J. E., van Duijn, H., de Groen, J. H., and van Duijn, M. A. (2002). Alcohol use, cigarette consumption and chronic post-traumatic stress disorder. *Alcohol and Alcoholism*, 37(4):355–361.

Orcutt, H. K., Bonanno, G. A., Hannan, S. M., and Miron, L. R. (2014). Prospective trajectories of posttraumatic stress in college women following a campus mass shooting. *Journal of Traumatic Stress*, 27(3):249–256.

Pals, J. L. and McAdams, D. P. (2004). The transformed self: A narrative understanding of posttraumatic growth. *Psychological Inquiry*, pages 65–69.

Pannenberg, M. (2010). Risk attitudes and reservation wages of unemployed workers: evidence from panel data. *Economics Letters*, 106(3):223–226.

Park, C. L. and Ai, A. L. (2006). Meaning making and growth: New directions for research on survivors of trauma. *Journal of Loss and Trauma*, 11(5):389–407.

Parsons, O. A. and Schneider, J. M. (1974). Locus of control in university students from eastern and western societies. *Journal of Consulting and Clinical Psychology*, 42(3):456.

Pearl, J. (2000). Causal inference without counterfactuals: Comment. *Journal of the American Statistical Association*, 95(450):428–431.

Pearl, J. et al. (2009). Causal inference in statistics: An overview. *Statistics surveys*, 3:96–146.

Picone, G., S. F. . T. D. (2004). Effects of risk and time preference and expected longevity on demand for medical tests. *Journal of Risk and Uncertainty*, 28(1):39–53.

Pieters, J. and Rawlings, S. (2016). Parental unemployment and child health in china. *Unpublished paper*.

Poutvaara, P. and Siemers, L.-H. R. (2008). Smoking and social interaction. *Journal of Health Economics*, 27(6):1503 – 1515.

Powdthavee, N. (2014). What childhood characteristics predict psychological resilience to economic shocks in adulthood? *Journal of Economic Psychology*, 45:84–101.

Prosser, L. A. and Wittenberg, E. (2007). Do risk attitudes differ across domains and respondent types? *Medical Decision Making*, 27(3):281–287.

Rajapaksa, D., Wilson, C., Managi, S., Hoang, V., and Lee, B. (2016). Flood risk information, actual floods and property values: a quasi-experimental analysis. *Economic Record*, 92:52–67.

Reltz, H. J., . G. G. K. (1974). Economic development and belief in locus of control among factory workers in four countries. *Journal of cross cultural psychology*, 5(3):344–355.

Richards, M. R. and Marti, J. (2014). Heterogeneity in the smoking response to health shocks by out-of-pocket spending risk. *Health Economics, Policy and Law*, 9(4):343–357.

Riley Jr, W. and Chow, K. V. (1992). Asset allocation and individual risk aversion. *Financial Analysts Journal*, 48(6):32–37.

Riphahn, R. T. (1999). Income and employment effects of health shocks a test case for the german welfare state. *Journal of Population Economics*, 12(3):363–389.

Roberts, B. W. (2007). Contextualizing personality psychology. *Journal of personality*, 75(6):1071–1082.

Roberts, B. W. (2009). Back to the future: Personality and assessment and personality development. *Journal of research in personality*, 43(2):137–145.

Roberts, B. W., Kuncel, N. R., Shiner, R., Caspi, A., and Goldberg, L. R. (2007). The power of personality: The comparative validity of personality traits, socioeconomic status, and cognitive ability for predicting important life outcomes. *Perspectives on Psychological science*, 2(4):313–345.

Roberts, M. E., Stewart, B. M., and Nielsen, R. (2015). Matching methods for high-dimensional data with applications to text. *Unpublished manuscript*.

Rocco, L. and d'Hombres, B. (2014). Social capital and smoking behavior. *Eastern Economic Journal*, 40(2):202 – 225.

Ronay, R. and von Hippel, W. (2010). Power, testosterone, and risk-taking. *Journal of Behavioral Decision Making*, 23(5):473–482.

Rose, G., Khaw, K.-T., and Marmot, M. (2008). *Rose's strategy of preventive medicine: the complete original text*. Oxford University Press, USA.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Rothman, A. J., Bartels, R. D., Wlaschin, J., and Salovey, P. (2006). The strategic use of gain-and loss-framed messages to promote healthy behavior: How theory can inform practice. *Journal of communication*, 56(s1).

Rothschild, M. and Stiglitz, J. E. (1970). Increasing risk: I. a definition. *Journal of Economic theory*, 2(3):225–243.

Rotter, J. B. (1954). Social learning and clinical psychology.

Rotter, J. B. (1966). Generalized expectancies for internal versus external control of reinforcement. *Psychological monographs: General and applied*, 80(1):1.

Rubin, D. B. (2001). Using propensity scores to help design observational studies: application to the tobacco litigation. *Health Services and Outcomes Research Methodology*, 2(3-4):169–188.

Rubin, D. B. and Thomas, N. (1996). Matching using estimated propensity scores: relating theory to practice. *Biometrics*, pages 249–264.

Rustichini, A., DeYoung, C. G., Anderson, J. E., and Burks, S. V. (2016). Toward the integration of personality theory and decision theory in explaining economic behavior: An experimental investigation. *Journal of Behavioral and Experimental Economics*, 64:122–137.

Sahm, C. R. (2012). How much does risk tolerance change? *The quarterly journal of finance*, 2(04):1250020.

Salamanca, N., de Grip, A., Fouarge, D., and Montizaan, R. M. (2013). Locus of control and investment in risky assets. *Unpublished paper*.

Samuelson, P. A. (1937). A note on measurement of utility. *The review of economic studies*, 4(2):155–161.

Sanchez, M.-A., Barnay, T., Marsaudon, A., and Rochaix, L. (2019). L'influence des accidents de la route sur les trajectoires professionnelles des personnels en fin de carrière, à partir de la cohorte Gazel. Erudite Working Paper 2019-11, Erudite.

Sapienza, P., Zingales, L., and Maestripieri, D. (2009). Gender differences in financial risk aversion and career choices are affected by testosterone. *Proceedings of the National Academy of Sciences of the United States of America*, 106(36):15268–73.

Sawyer, S. M., Afifi, R. A., Bearinger, L. H., Blakemore, S. J., Dick, B., Ezeh, A. C., and Patton, G. C. (2012). Adolescence: a foundation for future health. *The Lancet*, 379(9826):1630–1640.

Scharff, R. L. and Viscusi, W. K. (2011). Heterogeneous rates of time preference and the decision to smoke. *Economic Inquiry*, 49(4):959–972.

Schildberg-Hörisch, H. (2018). Are risk preferences stable? *Journal of Economic Perspectives*, 32(2):135–54.

Schipper (2014). sex hormone and choice under risk. *Mimeo, University of California.*

Schmid, K. L., Rivers, S. E., Latimer, A. E., and Salovey, P. (2008). Targeting or tailoring? maximizing resources to create effective health communications. *Marketing health services*, 28(1):32.

Schünemann, J., Strulik, H., and Trimborn, T. (2017). The gender gap in mortality: How much is explained by behavior? *Journal of health economics*, 54:79–90.

Schurer, S. (2014). Bouncing back from health shocks: Locus of control, labor supply, and mortality.

Schurer, S. (2015). Lifecycle patterns in the socioeconomic gradient of risk preferences. *Journal of Economic Behavior & Organization*, 119:482–495.

Sears, S. R., Stanton, A. L., and Danoff-Burg, S. (2003). The yellow brick road and the emerald city: benefit finding, positive reappraisal coping and posttraumatic growth in women with early-stage breast cancer. *Health Psychology*, 22(5):487.

Segan, C. J., Borland, R., and Greenwood, K. M. (2006). Can transtheoretical model measures predict relapse from the action stage of change among ex-smokers who quit after calling a quitline? *Addictive behaviors*, 31(3):414–428.

Seligman, M. E. (2008). Positive health. *Applied psychology*, 57:3–18.

Seligman, M. E. et al. (2002). Positive psychology, positive prevention, and positive therapy. *Handbook of positive psychology*, 2(2002):3–12.

Seligman, M. E., Rashid, T., and Parks, A. C. (2006). Positive psychotherapy. *American psychologist*, 61(8):774.

Seligman, M. E., Steen, T. A., Park, N., and Peterson, C. (2005). Positive psychology progress: empirical validation of interventions. *American psychologist*, 60(5):410.

Semykina, A. and Linz, S. J. (2007). Gender differences in personality and earnings: Evidence from russia. *Journal of Economic Psychology*, 28(3):387–410.

Shaw, K. L. (1996). An empirical analysis of risk aversion and income growth. *Journal of Labor Economics*, 14(4):626–653.

Sianesi, B. (2004). An evaluation of the swedish system of active labor market programs in the 1990s. *Review of Economics and statistics*, 86(1):133–155.

Skriabikova, O. J., Dohmen, T., and Kriechel, B. (2014). New evidence on the relationship between risk attitudes and self employment. *Labour Economics*, 30:176–184.

Slovic, P., Finucane, M. L., Peters, E., and MacGregor, D. G. (2004). Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk, and rationality. *Risk analysis*, 24(2):311–322.

Smith, J. A. and Todd, P. E. (2005). Does matching overcome lalonde's critique of nonexperimental estimators? *Journal of econometrics*, 125(1-2):305–353.

Smith, J. P. (1999). Healthy bodies and thick wallets: the dual relation between health and economic status. *Journal of Economic perspectives*, 13(2):145–166.

Smith, T. B., McCullough, M. E., and Poll, J. (2003). Religiousness and depression: Evidence for a main effect and the moderating influence of stressful life events. *Psychological bulletin*, 129(4):614.

Smith, V. K., Taylor Jr, D. H., Sloan, F. A., Johnson, F. R., and Desvousges, W. H. (2001). Do smokers respond to health shocks? *The Review of Economics and Statistics*, 83(4):675–687.

Spector, P. E., C. C. L. S. J. I. O. M. S. K. B. P. . and Miller, K. (2002). Locus of control and well-being at work: how generalizable are western findings? *Academy of Management Journal*, 45(2):453–466.

Srivastava, S., John, O. P., Gosling, S. D., and Potter, J. (2003). Development of personality in early and middle adulthood: Set like plaster or persistent change? *Journal of personality and social psychology*, 84(5):1041.

Stenstrom, E., Saad, G., Nepomuceno, M., and Mendenhall, Z. (2011). Testosterone and domain-specific risk: Digit ratios (2d: 4d and< i> rel</i> 2) as predictors of recreational, financial, and social risk-taking behaviors. *Personality and Individual Differences*, 51(4):412–416.

Stigler, G. J. and Becker, G. S. (1977). De gustibus non est disputandum. *The american economic review*, 67(2):76–90.

Stillman, S., Gibson, J., and McKenzie, D. (2012). The impact of immigration on child health: experimental evidence from a migration lottery program. *Economic Inquiry*, 50(1):62–81.

Sundmacher, L. (2012). The effect of health shocks on smoking and obesity. *The European Journal of Health Economics*, 13(4):451–460.

Takahashi, T., Sakaguchi, K., Oki, M., and Hasegawa, T. (2008). Sex hormonal modulation of hyperbolic discount factor in men. *Journal of Neuroscience, Psychology, and Economics*, 1(1):7.

Tang, T. Z., DeRubeis, R. J., Hollon, S. D., Amsterdam, J., Shelton, R., and Schalet, B. (2009). Personality change during depression treatment: a placebo-controlled trial. *Archives of general psychiatry*, 66(12):1322–1330.

Tedeschi, R. G. and Calhoun, L. G. (1996). The posttraumatic growth inventory: Measuring the positive legacy of trauma. *Journal of traumatic stress*, 9(3):455–471.

Tedeschi, R. G. and Calhoun, L. G. (2004). " posttraumatic growth: Conceptual foundations and empirical evidence". *Psychological inquiry*, 15(1):1–18.

Tennen, H. and Affleck, G. (2009). Assessing positive life change: In search of meticulous methods.

Tennen, H., Affleck, G., Urrows, S., Higgins, P., and Mendola, R. (1992). Perceiving control, construing benefits, and daily processes in rheumatoid arthritis. *Canadian Journal of Behavioural Science/Revue canadienne des sciences du comportement*, 24(2):186.

Trevisan, E. and Zantomio, F. (2016). The impact of acute health shocks on the labour supply of older workers: Evidence from sixteen european countries. *Labour Economics*, 43:171–185.

Tusicisny, A. (2017). Reciprocity and discrimination: An experiment of hindu muslim cooperation in indian slums. *Political Psychology*, pages 409–426.

Van Der Pol, M. (2011). Health, education and time preference. *Health economics*, 20(8):917–929.

Van Der Pol, M., Hennessy, D., and Manns, B. (2017). The role of time and risk preferences in adherence to physician advice on health behavior change. *The European Journal of Health Economics*, 18(3):373–386.

van Honk, J., Schutter, D. J., Hermans, E. J., Putman, P., Tuiten, A., and Koppeschaar, H. (2004). Testosterone shifts the balance between sensitivity for punishment and reward in healthy young women. *Psychoneuroendocrinology*, 29(7):937–943.

Van Praag, C. M. and Cramer, J. S. (2001). The roots of entrepreneurship and labour demand: Individual ability and low risk aversion. *Economica*, 68(269):45–62.

Viscusi, W. K. (1992). *Fatal tradeoffs: Public and private responsibilities for risk*. Oxford University Press.

Wagner, G. G., Frick, J. R., and Schupp, J. (2007). The german socio-economic panel study (soep)–scope, evolution and enhancements, 161–191. *Google Scholar*.

Watson, D. and Hubbard, B. (1996). Adaptational style and dispositional structure: Coping in the context of the five factor model. *Journal of personality*, 64(4):737–774.

Weber, E. U., Blais, A.-R., and Betz, N. E. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of behavioral decision making*, 15(4):263–290.

Weber, E. U., Böckenholt, U., Hilton, D. J., and Wallace, B. (1993). Determinants of diagnostic hypothesis generation: Effects of information, base rates, and experience. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 19(5):1151.

Weidner, G. (2000). Why do men get more heart disease than women? an international perspective. *Journal of American College Health*, 48(5-6):291–294.

WHO (2018). Global health estimates 2016: deaths by cause, age, sex, by country and by region, 2000–2016. *World Health Organization*.

Wooldridge, M., Jennings, N. R., and Kinny, D. (2000). The gaia methodology for agent-oriented analysis and design. *Autonomous Agents and multi-agent systems*, 3(3):285–312.

Wu, S. (2003). The effects of health events on the economic status of married couples. *Journal of Human Resources*, 38(1):219–230.

Zimmer, D. M. (2015). Employment effects of health shocks: The role of fringe benefits. *Bulletin of Economic Research*, 67(4):346–358.

Appendix

Table A1: Summary of the existing studies on the relationship between health shocks and labor, health, and wealth outcomes in developing countries

Type of health shocks	Scope	Outcomes impacted	Distribution	Nb. of studies
Deterioration in physical functioning abilities	Idiosyncratic	Wealth, Health, Labor	Indonesia, Vietnam, Ethiopia	4
Births, deaths, disability, illness, accident and surgery	Idiosyncratic	Health	Pakistan, Laos, Ethiopia	3
Treatment for HIV/AIDS; Being HIV/AIDS infected; Loss of weight	Idiosyncratic	Wealth	Kenya, Namibia	2
Injury in the past two weeks	Idiosyncratic	Health	Zambia, Vietnam	2
Household's total medical expenditure not covered by health insurance	Idiosyncratic	Health	Vietnam, Bangladesh	2
Any household member that was sick; Number of sickness day; Number of day work loss due to sickness; Death of the main earner in the family	Idiosyncratic	Wealth, Health, Labor	Bangladesh, Vietnam	2
Maternal and child illness	Idiosyncratic	Wealth	Vietnam	2
Drop in a scale of self-reported health	Idiosyncratic	Wealth	Ethiopia	1
Road accident, diarrhea, asthma attack, hypertension and diabetes	Idiosyncratic	Wealth	Jamaica	1
Malaria	Covariate	Wealth	Tanzania	1
Arsenic poisoning of water	Covariate	Health	Bangladesh	1

Note: the most common type of health shock used in developing countries is a deterioration in physical abilities, the country that received the more attention is Vietnam, and the most often outcome of interest is wealth. A shock is considered as idiosyncratic if it affects only some individual, and covariate if it affects a large part of a population (Dercon et al. (2005)).

Table A2: Summary of the existing studies on the relationship between health shocks and labor, health, and wealth outcomes for the BRICSAM[113] countries

Type of health shocks	Scope	Outcomes impacted	Distribution	Nb. of studies
2009 H1N1 pandemic	Covariate	Health	Mexico	1
Hospital stays	Idiosyncratic	Wealth	Mexico	1
Changes in the health status of the head and his/her spouse;				
Number of days during which another household members report severe illness	Idiosyncratic	Wealth	Mexico	1
Bus accident injuries	Idiosyncratic	Wealth	India	1
Abnormal increase in a household medical expenditures	Idosyncratic	Labor	China	1

Note: Here is no particular types of health shock used for the BRICSAM countries, the country had received the more attention is Mexico, and the most often outcome of interest is wealth.

[113] BRICSAM stands for Brazil, Russia, India, China, South Africa, and Mexico.

Table A3: Summary of the existing studies on theoretical impacts of health shocks

Type of health shocks	Assumption	Outcomes	Predictions	Nb. of studies
Obesity epidemic	Health shock is endogenously determined by an agent's calorie choice	Health asset portfolios	Wealthier individuals have lower morbidity rates	1
Cancer	Health shock is permanent so that agents cannot recover	Labor income	Individual reduce their long-term insurance demand	1
Expensive health costs	A household utility is defined as a function of human capita, a house and other fixed assets, cash and other financial assets, and land and other productive asset	Welfare and portfolio decision-making	For asset-rich household, the health shock induces medical treatment. For asset-poor household, the health shock does not induce treatment	1

Note: all theoretical studies predict a negative impact of health shocks (no matter its modeling, not matter the outcomes of interest).

Table A4: Summary of the existing studies on the relationship between health shocks and peer effects

Type of health shocks	Whose benefit?	Results	Distribution	Nb. of studies
Parental illness	Child educational attainment	Father's illness decreases children's school attendance; no effect of mother's illness.	Tanzania	1
Pest infestation of parents	Child time school and home production	Increase children's number of hours worked in household and childcare	Mali	1
Health shock on a twin	Other twin health and educational attainment	Reduce educational attainment but increase health expenditures	China	1
Household report major illness (injuries or accidents)	Child educational attainment attainment	Reduce primary school attainment	China	1
Exposure to Spanish flu during pregnancy	Child educational attainment	Reduce average years of schooling	Italy	1
Chest/breathing and heart/blood pressure of a smoker household member	Other household member	Little negative effect on smoking	British	1
Parental health shock	Child Health	Negative effect of maternal health shocks on children's emotional symptoms; conduct problems; and hyperactivity; Paternal seems to be less relevant to children's behaviors	Germany	1
Mother mental health (depression; anxiety)	Child Health	No impact on child general health; asthma morbidity; anthropometric measures; Impact food and digestive allergies and tonsillitis incidence	Australia	1
Fetal mother shocks	Child Health	Lower weight	South Africa and US	1
Smoking related cardiovascular events	Child smoking status	Daughter reduce both their smoking participation and intensity; and they also report worse health following a parental death	US	1

Note: Most of studies analyze the impact of parent health shocks on their children educational attainment or health. All types of shocks reduce children outcomes.

Table B1: Summary of the existing studies on the relationship between shocks and risk tolerance in developing countries

Type of health shocks	Measure of risk tolerances	Population	Results
Violent conflicts (war-related death)	Risk preferences (Harbaugh et al. (2002) measure)	Burundi	Increase risk-seeking
Flood	Risk preferences (Binswanger (1980) measures)	Cambodia	Increase risk-aversion
Demographic (e.g. illness), social (e.g. ceremony), agricultural (e.g. drought), and economic (e.g. price increase for inputs) shocks	Risk attitude (Dohmen et al. (2011) measures)	Thailand and Vietnam	Increase risk-aversion
Tsunami	Risk preferences (based on Holt and Laury (2002) measure)	Thailand	Increase risk-aversion
Successful attacks (i.e. direct fire, improvised explosive devise explosions, indirect fire, mine strikes, and suicide attacks) and unsuccessful attacks (improvised explosive devices found and cleared, improvised explosive device hoaxes, and mines found and cleared)	Risk preferences (Andreoni and Sprenger (2011) measure)	Afghanistan	Increase risk-aversion

Note: Impact of shock in developing countries seems to increase risk aversion, with the exception of one paper. For a review of experimental and survey measures of risk, time, and social preferences, the reader can refer to Chuang and Schechter (2015).

Table B2: Summary of the existing studies on the relationship between shocks and risk tolerance in developed countries

Type of health shocks	Measure of risk tolerances	Population	Results
Flood	Risk attitudes (Rajapaksa et al. (2016) measures)	Australia	Increase risk aversion
Great East Japan earthquake	Risk preferences (Hanaoka et al. (2018) measures)	Japan	Increase risk-seeking
Hurricane	Risk preferences (Eckel and Grossman (2002) measures)	US	Increase risk-seeking
Experiencing large wealth variation	Detention of risky assets (i.e. stocks and share, corporate bonds, and mutual funds)	Italy	Constant
Experiencing large wealth variation	Detention of risky assets (i.e. sum of stocks and mutual funds divided by liquid assets; and the sum of stocks and mutual funds, home equity, divided by financial wealth)	US	Constant
Acute (i.e. cancer, stroke, heart problems) and chronic (i.e. lung problems, diabetes, high blood pressure, arthritis, psychological problems)	Percentage of risky assets	US	For men, neuroticism has a positive effect on risk tolerance. For men and women, conscientiousness has a positive influence on risk tolerance. Agreeableness and openness to experience affect risk tolerance of men in couple.

Note: The impact of non-health shocks on risk tolerance shows mixed results (either an increase in risk aversion or a constant relationship).

List of Figures

List of Tables

Abstract / Résumé

Impact d'un choc de santé sur les préférences économiques, les traits de personnalité et les comportements de santé

Résumé : Pour limiter l'incidence croissante des maladies chroniques, un grand nombre de pays de l'OCDE ont mis en place des politiques de prévention et d'information axées sur les changements de comportement de santé. Toutefois, ces mesures peuvent encore être améliorées car certaines des populations à risque peinent à modifier significativement et durablement leur comportement. Au-delà des différences inter-individuelles sur lesquelles sont fondées la plupart de ces interventions, les variations intra-individuelles sont également à considérer lors de l'élaboration des politiques publiques. L'expérience du système de santé a-t-elle induit un changement des préférences ou des traits de personnalité de l'individu ? Ces deux paramètres se forment-ils après avoir connu un événement de santé important ? En utilisant des données de panel et en mobilisant les outils économétriques, les résultats montrent que les individus ayant connu un événement important de santé vont modifier, sensiblement, certain de leurs traits de personnalité (chapitre 1). À l'inverse, un tel événement n'induit pas de changement dans les préférences économiques (chapitre 2). Ainsi, un événement de santé n'est pas être déterminant dans la formation des préférences, mais l'est pour certains traits de personnalité. Les préférences économiques ne sont pas non plus déterminées *in-utero* (chapitre 3). Par ailleurs, les individus subissant un événement de santé adoptent de meilleurs comportements de santé (chapitre 4).
Mots-clefs : événement de santé; données longitudinales; préférences économiques; traits de personnalité; comportements de santé.

Impact of health shocks on economic preferences, personality traits and health behaviors

Abstract: This PhD dissertation aims to document whether personality traits and economic preferences are stable parameters after the occurrence of a significant health event. Given the massive impacts of traits and preferences on life outcomes, it is necessary to provide information as to how much these can change. Results show that traits are slightly modified when individuals face a health event (Chapter 1). Economic preferences, however, do not change after the occurrence of such events (Chapter 2). The finding that preferences are stable might call for a genetic transmission of these parameters. However, results show that economic preferences are not determined *in-utero* (Chapter 3). Additionally, individuals facing health events are more likely to adopt healthier behaviors than those who do not face such events (Chapter 4). These findings can be used by economic researchers and policymakers. For the former, relying solely upon individual fixed-effect estimations or first difference methods might not account for trait variation. For the latter, changes in traits might modify the willingness to invest in various health, education and labor outcomes, subsequently influencing macroeconomic performance.
Keywords: health shocks; panel data; economic preferences; personality traits; health behaviors.