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# Investment in preventive health and Behavioral biases

Clémence Pougué-Biyong

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U.F.R. DE SCIENCES ÉCONOMIQUES  
Centre d'Économie de la Sorbonne

*Thèse pour l'obtention du titre de Docteur en Économie  
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## **Investment in preventive health and Behavioral biases**

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# Investment in preventive health and Behavioral biases

by Clémence Pougé Biyong

Healthcare systems that primarily rely on out-of-pocket payment by users — such as the majority of systems in low and middle-income countries— tend to underinvest in preventive health. This thesis explores the effects of this underinvestment through the lens of behavioral biases. Chapter 1 shows that between 2000 and 2016 in Malawi, individuals exposed to foreign aid-funded HIV prevention programs did not screen significantly more than those who were not exposed. However, stigma increased in areas that were exposed to such programs. Chapter 2 analyzes the adoption of preventive treatment with a discrete choice model that incorporates a risk behavior parameter. The theoretical stylized facts are then tested using a simultaneous equations model and a novel longitudinal database collected among female sex workers in Côte d’Ivoire. This study shows that the decision to adhere to preventive treatment depends on the level of risk in sexual behavior and suggests better comprehending the threat of risk compensation behavior. In the context of rising obesity rates, Chapter 3 analyzes the effect of a tax on sugar-sweetened beverages as an in-utero shock on children’s health in Mexico. This chapter shows that tax policy is not sufficient to change mothers’ nutritional behavior and improve children’s health. Finally, the last chapter was written and published in the midst of the Covid-19 pandemic to predict the spread of the virus in Ghana, Kenya, and Senegal. It proposes a susceptible-infected-recovered model taking into account the time-invariant characteristics of the countries studied and the heterogeneity of the infectious status of individuals. This chapter shows that having a young and mainly rural population limits the spread and severity of the pandemic in the countries studied.

**Keywords:** preventive health, behavioral biases, risky behavior, HIV, obesity, Covid-19.

**JEL Classification:** I1, D01, D9, H20.



À la mémoire de Papa et Lydie.



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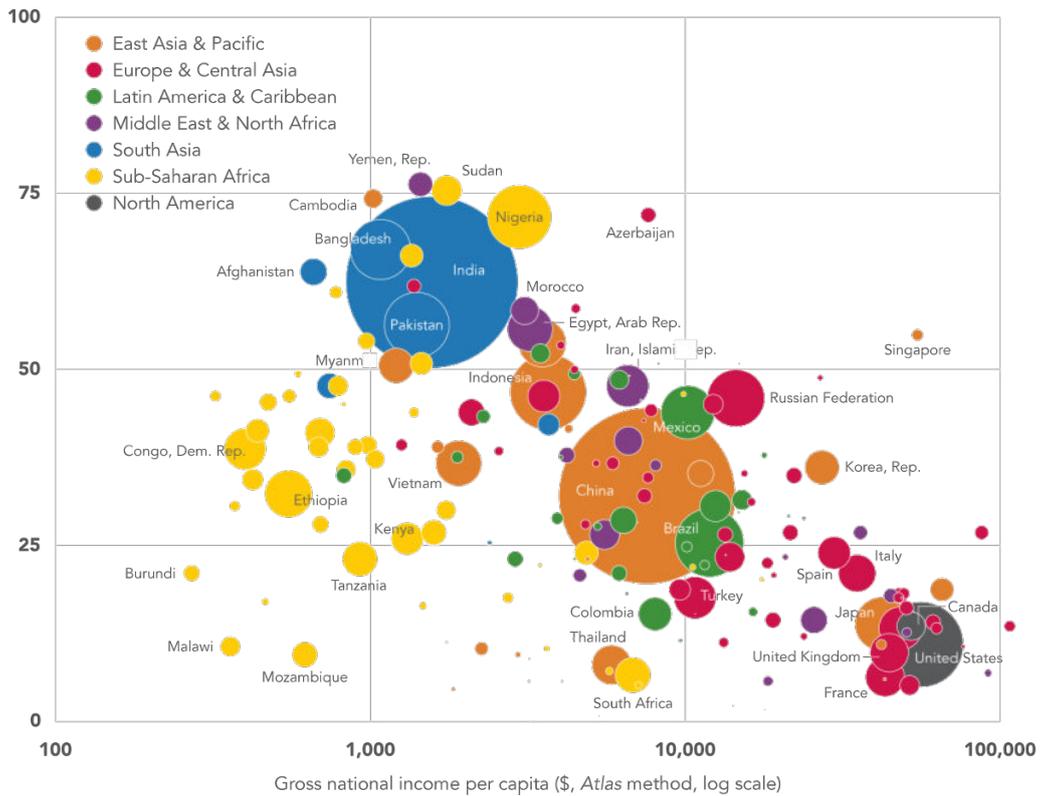
À mon frère John, seul l'amour peut relever une âme et lui apporter une confiance qu'elle pense avoir perdu. Thank you is not enough. I believe this thesis is only another chapter on our journey together. Love.



## Introduction générale

En Août 2022, l'Organisation Mondiale de la Santé (OMS) a annoncé que l'espérance de vie en Afrique a augmenté d'environ dix ans entre 2000 et 2019 ([World Health Organization. Regional Office for Africa 2022](#)). “La prévention et le traitement des maladies infectieuses” ont été les principaux déterminants de cette progression. Au delà de l'allongement de l'espérance de vie, la santé préventive participe aussi à la réalisation de l'Objectif n3 des Objectifs du Développement Durable (ODD) : “Permettre à tous de vivre en bonne santé et promouvoir le bien-être de tous à tout âge sont des conditions essentielles au développement durable.” Malheureusement, il est difficile d'atteindre cet objectif dans les régions du monde où les politiques publiques de santé restent faibles et où par conséquent le reste-à-charge est encore la principale source de financement des systèmes de santé. D'après la figure 1, cette menace concerne principalement les pays à revenu faible et intermédiaire (PRFI).

FIGURE 1: Reste-à-charge dans les dépenses totales de santé (2014)

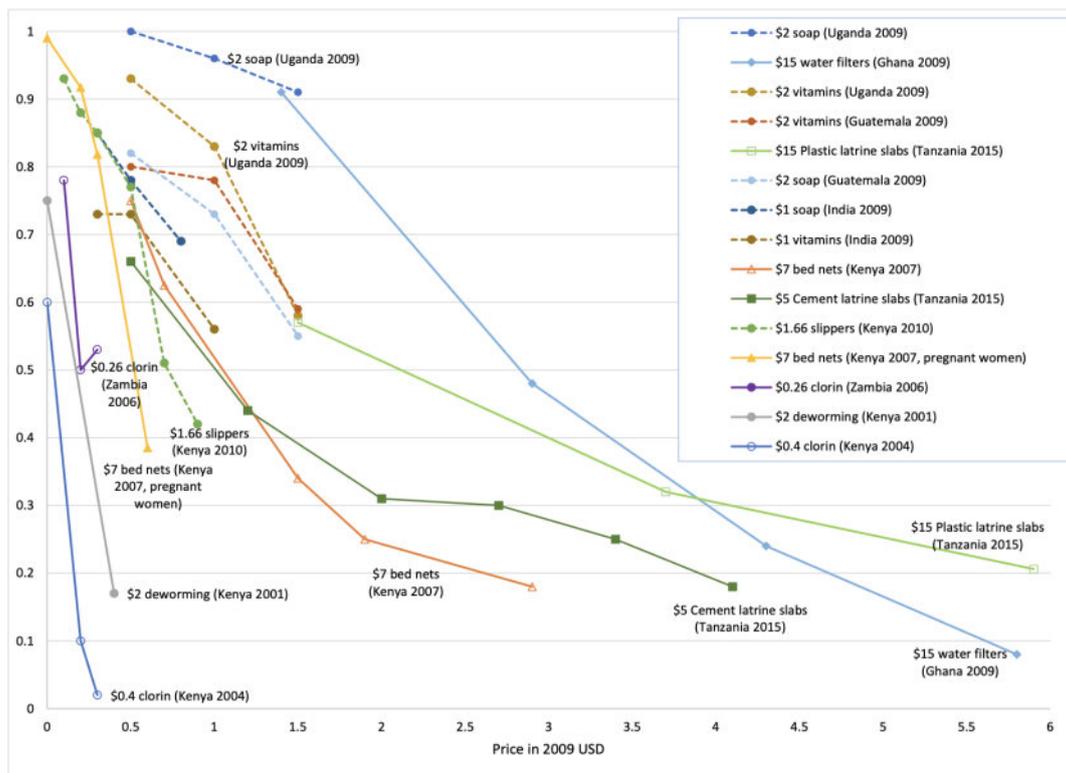


Note : Proportion de reste-à-charge dans les dépenses totales de santé par pays. La taille de chaque cercle est proportionnelle à la population du pays.

Source : Le graphique est réalisé par le Groupe de la Banque Mondiale sur la base des données de l'OMS Global Health Expenditure ; World Bank National Accounts database ; OECD National Accounts database et WDI.

Dans ce contexte, les dépenses de santé sont une responsabilité individuelle, et investir en santé préventive implique de prendre en charge de nombreux coûts directs et indirects. Dans les PRFI en Afrique, Dupas and Miguel (2017) observent un sous-investissement significatif dans la santé préventive y compris lorsque les médicaments sont gratuits (voir la figure 2).

FIGURE 2: Demande pour les produits de santé préventive au Ghana, Kenya, Tanzanie, Ouganda et Zambie



Note : Le graphique représente l'investissement en santé préventive au Ghana, Kenya, Tanzanie, Ouganda et Zambie. L'axe des ordonnées représente la part des individus et des ménages qui adoptent le produit. L'axe de abscisses donne le prix en dollars constants année 2000. Source : Dupas and Miguel (2017).

Selon Kremer et al. (2019), les modèles microéconomiques canoniques n'apportent pas les clés d'analyse de ce sous-investissement en santé préventive. Pour dépasser ces limites théoriques, des travaux récents en économie comportementale du développement sont consacrés à et encouragent la recherche sur le sous-investissement en santé préventive (Kremer et al. 2019, Dupas and Miguel 2017).

L'objectif de cette thèse est de contribuer à ces travaux en proposant quatre chapitres sur les relations entre l'investissement en santé préventive et les biais comportementaux. Chaque chapitre soulève une question de recherche unique à laquelle je réponds en m'appuyant sur des analyses empiriques et des bases de données différentes. Parce qu'ils présentent des résultats dans des contextes spatio-temporels différents, les chapitres peuvent sembler éloigner les uns des autres. Pourtant, chaque chapitre propose une contribution pour répondre à une limite du chapitre qui le précède et améliorer la compréhension des liens entre l'investissement en santé préventive et les biais comportementaux.

Pour délimiter les enjeux du sujet, les termes sont définis dans la section 1 et le contexte est décrit dans la section 2. Les problématiques sont présentées dans la section 3. Un rappel de la littérature dans la section 4 mettra en perspective les apports de cette thèse, présentés dans la section 5.

## 1 Définir l’investissement en santé préventive et les biais comportementaux

Le sujet “Investissement en santé préventive et biais comportementaux” peut amener à différentes questions de recherche. La section suivante définit chaque termes du sujet pour en délimiter la portée.

En premier lieu, la santé peut être entendue de deux façons complémentaires. Au sens restrictif, l’Organisation Mondiale de la Santé définit la santé comme “un état de complet bien-être physique, mental et social et [qui] ne consiste pas seulement en une absence de maladie ou d’infirmité” ([World Health Organization 1948](#)). La santé est donc multidimensionnelle et subjective. Elle évolue en fonction de la présence ou non d’une maladie, du ressenti de la douleur ou de l’évolution des symptômes. Surtout, la santé est un état complet, qui intègre les paramètres physiques et psychiques au même niveau. Bien que cette thèse présente principalement des mesures de la santé physique, elle encourage la recherche sur la santé préventive à intégrer les autres aspects de la santé.

Au sens plus large, la santé dépasse sa définition anthropocentrée et individuelle ; elle concerne également la communauté. On entendra alors la santé comme la santé globale, mais uniquement relative aux êtres humains. Ainsi, [Koplan et al. \(2009\)](#) définissent la santé comme “le domaine de recherche et de pratique qui mobilise des approches multidisciplinaires, multisectorielles et culturelles pour réduire les disparités de santé qui transcendent les frontières nationales.” Les dernières avancées et l’urgence climatique nous invitent également à considérer la santé comme un tout intégrant les autres êtres vivants, le “One Health” ([WHO 2017](#)). Dans le cadre de cette thèse, la santé globale guidera chaque chapitre à se placer à l’intersection entre la microéconomie, l’économie de la santé et les politiques publiques. Ainsi, le Chapitre 1 mesure les effets des programmes de prévention financés par l’aide internationale sur le dépistage du VIH au Malawi. Le Chapitre 2 analyse l’accès à un médicament préventif contre le VIH (la prophylaxie pré-exposition, PrEP), pour des travailleuses du sexe en Côte d’Ivoire. Le Chapitre 3 interroge les conséquences d’une politique fiscale sur la consommation de boissons sucrées et la santé infantile.

Cette définition de la santé intègre un paramètre temporel lorsqu'elle est qualifiée de "préventive". L'objectif de la santé préventive est de "produire de la santé" avant qu'une maladie ne survienne (Cohen and Henderson 1988). On identifie trois types de prévention, qui seront abordées différemment dans les chapitres. La prévention primaire désigne les "actions qui ont pour objectif d'éviter la survenance d'une maladie" (Cohen and Henderson 1988). La prévention secondaire caractérise les actions de dépistage précoce pour accroître les chances d'avoir un niveau de santé positif. La prévention tertiaire implique la gestion de la progression des symptômes pour garantir la qualité de vie du patient. Les Chapitres 2 et 3 relèvent de la santé préventive primaire. Ils s'intéressent à l'évitement de la survenance de la maladie par l'adoption d'un traitement préventif en Côte d'Ivoire (Chapitre 2) ou d'un nouveau comportement nutritionnel au Mexique (Chapitre 3). Les Chapitres 1 et 4 sont reliés à la prévention secondaire, respectivement au dépistage du VIH au Malawi (Chapitre 1) et à la prédiction de la propagation du Covid-19 au Ghana, Kenya et Sénégal (Chapitre 4). L'étendue de la santé préventive est large, allant de la nutrition à la vaccination, au comportement sexuel, en passant également de façon plus prosaïque, mais non moins importante, par la "gestion de la maladie chronique" (Dupas and Miguel 2017). Bien que cette thèse n'aborde pas la prévention de la maladie chronique, elle espère contribuer à la recherche dans ce domaine.

Ainsi, en théorie tout investissement en santé préventive devrait être bénéfique pour la santé. Grossman (1972) définit la santé comme un "bien capital durable". Chaque individu dispose d'un stock de santé qui déprécie à travers le temps et qui, en dessous d'un certain seuil, se conclut par la mort. Il est possible d'accroître ce stock en investissant dans des réserves. Les ressources pour investir sont pécuniaires et non pécuniaires. Cet investissement peut être réalisé d'un point de vue individuel et microéconomique ou du point de vue institutionnel et des politiques publiques. Cette thèse s'attèle à comprendre comment l'investissement individuel et l'investissement public s'articulent pour favoriser la santé préventive. Ainsi le Chapitre 1 discute l'efficacité des dépenses des politiques publiques préventives pour le VIH par rapport à l'investissement individuel qui est la décision de se faire dépister. De même, le Chapitre 3 observe l'effet qu'une politique fiscale a sur le comportement nutritionnel et sur la santé des enfants. Cependant, l'investissement en lui-même est limité par la disponibilité des ressources.

D'un point de vue microéconomique, la figure 2 montre qu'il existe pourtant un sous-investissement en santé préventive même lorsqu'il existe un "fort retour sur investissement" (Kremer et al. 2019). Dans le modèle canonique de l'*homo econo-*

*micus*, la santé est un bien supérieur tel qu'il ne peut être soumis à un quelconque arbitrage pouvant se solder par un non-investissement (Cohen and Henderson 1988). Pourtant, les biais comportementaux peuvent expliquer ce sous-investissement. Pour l'économie néo-classique, le biais comportemental est entendu comme une action individuelle sous-optimale à niveau d'information donné, autrement dit un comportement irrationnel. Pour l'économie comportementale, dans laquelle s'inscrit cette thèse, le biais comportemental est "une distorsion du comportement qui a des traits universels du comportement humain" (Kremer et al. 2019). Autrement dit, le biais comportemental n'est pas nécessairement irrationnel. La littérature identifie différents biais comme le biais pour le présent, la naïveté, l'aversion à la perte, les préférences sociales, le biais de projection ou les fausses croyances... et cette thèse n'a pas pour objectif d'en définir de nouveaux.

Cette thèse fait une contribution empirique à l'analyse du rôle des biais comportementaux dans l'investissement en santé préventive dans les pays à revenu faible et intermédiaire. Précisément, les chapitres analysent le biais comportemental comme un obstacle à la santé préventive ou comme une externalité de politique publique. Les conclusions du Chapitre 1 suggèrent que la stigmatisation interfère avec la décision de dépistage VIH. Le Chapitre 3 estime l'effet d'une politique fiscale sur les comportements nutritifs dans un contexte de rareté. Le Chapitre 2 propose plutôt de questionner l'existence d'un biais comportemental et son lien avec la politique publique préventive, en complétant les recherches récentes sur le comportement de compensation des risques et la prévention contre le VIH au sein des travailleuses du sexe.

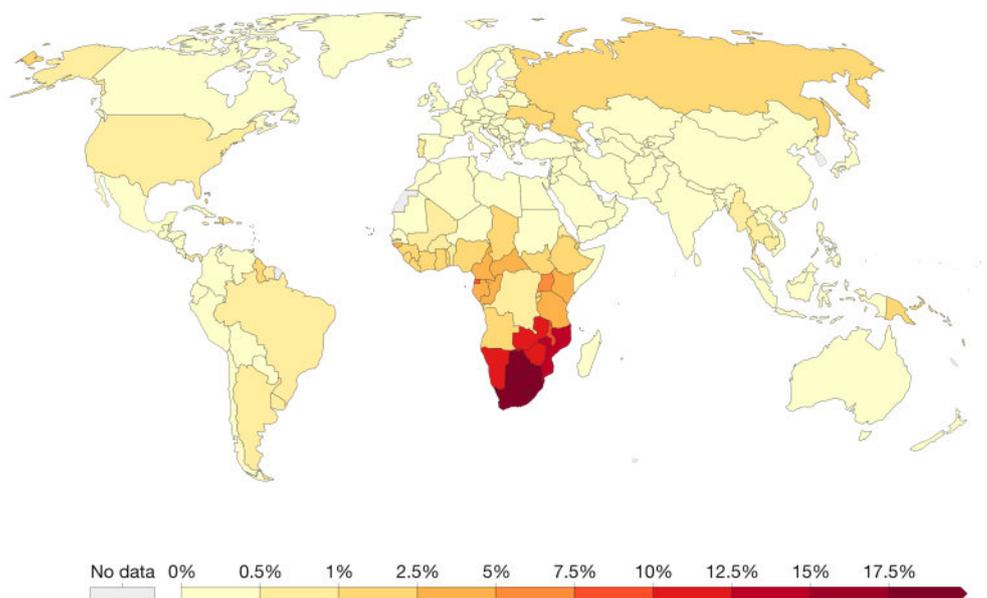
Enfin, il faut noter que le biais comportemental s'entend différemment pour les politiques publiques, au delà de la recherche en économie. Par définition, le biais s'oppose à la norme et la norme peut désigner le comportement standard ou moyen. Le biais peut être assimilé à un comportement marginal, ce qui n'est pas le cas de l'économie comportementale qui présente le biais comme une distorsion comportementale universelle. Chaque chapitre formule des recommandations de politiques publiques en prenant en compte l'enjeu épistémologique des biais comportementaux.

## **2 Le contexte : les pays à revenu faible et intermédiaire**

Cette thèse s'intéresse à l'investissement en santé préventive et aux biais comportementaux dans les pays à revenu faible et intermédiaire (PRFI), particulièrement dans

des pays en Afrique (Côte d'Ivoire, Ghana, Malawi, Kenya, and Sénégal). A cause d'un fort taux de reste-à-charge, les systèmes de santé de ces pays sont structurellement dépendants des décisions individuelles d'investissement en santé préventive, comme le montre la Figure 1. La prévalence et l'incidence de certaines maladies vont directement renforcer l'urgence de l'investissement en santé préventive. Ainsi, les Chapitres 1 et 2 se concentrent sur les comportement de santé dans des pays ayant les plus forts taux d'incidence et prévalence VIH, localisés en Afrique (voire Figure 3).

FIGURE 3: Taux de prévalence du VIH, en 2019



Note : Ce graphique présente la carte du taux de prévalence VIH par pays, calculé à partir d'un échantillon représentatif des hommes et femmes âgés de 15 à 49 ans.

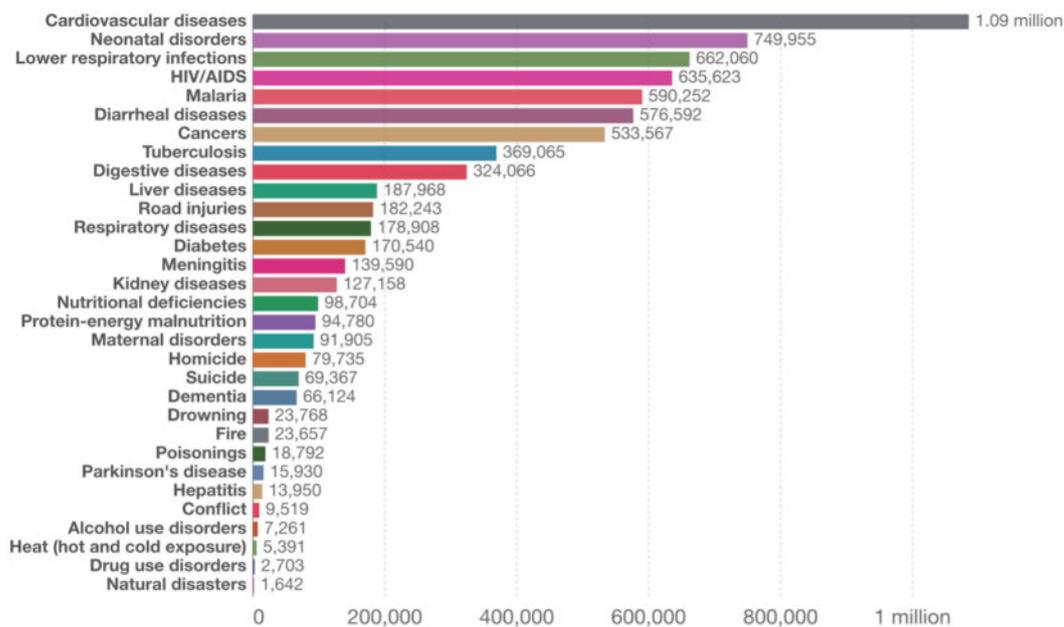
Source : [Roser and Ritchie \(2018\)](#) sur la base de Health Metrics and Evaluation (IHME)

De même, le Chapitre 4 s'appuie sur les similarités de la structure démographique dans différents pays d'Afrique - la jeunesse et la ruralité - pour identifier les déterminants de la propagation du Covid-19. Pour autant, si cette thèse s'intéresse à différents pays sur le continent africain, il est crucial de souligner les différences majeures entre chacun d'entre eux. Chaque pays reste unique et distinct bien que la colonisation ait défini différents Etats avec des caractéristiques culturelles et géographiques proches. Par conséquent, certains événements et tendances historiques dépassent les frontières pour laisser un héritage commun, de façon intentionnelle ou non, en termes de santé globale, de santé préventive et de biais comportementaux, comme pour la propagation du VIH ([Oster 2005](#), [2012a](#), [Anderson 2018](#), [Djemai](#)

2018).

Le Chapitre 3 se démarque géographiquement en ce qu'il se concentre sur l'impact de la taxation des boissons sucrées sur la santé des enfants au Mexique. Cette politique a été adoptée dans 54 pays, mais seulement quatre pays en Afrique (Afrique du Sud, Maurice, Nigéria et Seychelles), pour lutter contre la consommation de sucre. Pourtant, les maladies liées à cette malnutrition (maladies cardiovasculaires, diabète et obésité) sont les principales causes de décès sur le continent africain (voir la figure 4). De plus, en 2019, 24% des enfants de moins de cinq ans en surpoids vivaient sur le continent africain (WHO 2022). Dans un contexte où la pandémie de Covid-19 a révélé une partie de l'ampleur des risques associés la prévalence de l'obésité et de l'hypertension, on espère que la contribution de cette recherche au Mexique puisse servir les pays en Afrique.

FIGURE 4: Nombre de décès par cause, Région Afrique (OMS), 2019



Note : Ce graphique représente la décomposition des principales causes de décès, selon le nombre de décès par an.

Source : [Ritchie and Roser \(2018\)](#) sur la base de Institute for Health Metrics and Evaluation (IHME), Global Burden Disease.

### 3 Motivations

Ayant émergé il y a une vingtaine d'année, l'économie comportementale du développement, appelle à de nouvelles contributions pour comprendre le sous inves-

tissement en santé préventive (Kremer et al. 2019). Contribuer à cette littérature participe à l'amélioration de modèles économiques théoriques qui sont nécessaire à la compréhension de la demande de santé dans les PRFI. Cohen and Henderson (1988) résume ainsi :

*“L'intérêt des modèles théoriques est d'améliorer la compréhension des facteurs qui encouragent la demande en santé préventive, pour ensuite servir les politiques publiques, mais l'intérêt de ce service ne tient qu'à la qualité de l'analyse sur laquelle elle repose. Supposons que d'importants paramètres de la prévention soient omis [...]. Dans ce cas, on pourrait faire échouer des politiques publiques.”*

Bien que le sujet ait toujours été présent en économie de la santé, il n'est pas très répandu dans la littérature en économie du développement et au delà. Depuis 1992, *Health Economics* a publié 1 416 articles de recherche comprenant le terme “prévention” dans le texte, dont 42 ayant le terme dans les mots clés et 44 dans le titre. Le *Journal of Development Economics* a 110 publications avec le terme “prévention”, associé ou non à la santé, depuis 1996 et dont plus de 10% datent de 2020, l'année de la pandémie de Covid-19. L'*American Economics Association* a seulement 18 publications en santé avec les termes clés “prévention” ou “préventif”, toutes revues confondues. Ce n'est qu'au printemps 2021 que le *Journal of Economic Perspectives* a publié un article sur la santé préventive (Newhouse 2021).

L'investissement en santé préventive a toujours été un enjeu de politique publique mais n'en a jamais été la priorité à cause de son coût (Newhouse 2021). La santé préventive est couteuse, car son champ d'intervention est très large et peut impliquer des domaines aussi divers que la nutrition, le dépistage ou les médicaments préventifs. Les ressources sont limitées en comparaison à d'autres postes de dépense en santé ou pour des systèmes qui ayant déjà des ressources limitées n'en font pas leur priorité (Cohen and Henderson 1988).

Depuis la pandémie de Covid-19 en 2020, les organisations internationales ont repositionné la santé préventive comme un enjeu de santé publique majeur, particulièrement d'un point de vue comportemental <sup>1</sup> A la faveur de la lutte contre la pandémie de Covid-19, le comportement individuel est devenu le premier maillon de la chaîne préventive, incluant la distanciation sociale et le lavage des mains par exemple. Certains biais comportementaux relatifs à l'absence de confiance, la

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<sup>1</sup>Voir la communication de M. van Nieuwkoop, Directeur Mondial, Département Agriculture et Pratiques Alimentaires Mondiales, Banque Mondiale, et M. Eloit, Directeur Général de l'Organisation Mondiale de la Santé Animale.

désinformation, ou la mauvaise analyse des informations, ont également été révélés par la pandémie. Cette thèse a contribué à prévenir la propagation du Covid-19 dans certains pays en Afrique avec le Chapitre 4, bien qu'il ne fut pas concentré sur le rôle des biais comportementaux dans la pandémie. Le Chapitre 4 a été rédigé au coeur du premier confinement mondial pour prédire la propagation de l'épidémie au Ghana, au Kenya et au Sénégal.

**Par conséquent, la problématique de cette thèse est de déterminer dans quelle mesure une politique publique peut être efficace lorsque les biais comportementaux interfèrent avec l'investissement en santé préventive. Elle s'articule à travers les questions suivantes : Dans quelle mesure l'investissement en santé préventive est limité par les biais comportementaux ? Dans quelle mesure le sous investissement en santé préventive peut être rationnel ? Dans quelle mesure une politique publique peut réduire les comportements de malnutrition, souvent lié à des biais comportementaux ?**

## 4 Revue de la littérature

L'investissement en santé préventive est le résultat d'une analyse coût-bénéfice que certains individus ne peuvent pas effectuer à cause de différents biais comme l'incertitude ou les fausses croyances. [Arrow \(1963\)](#) est le premier à mettre en évidence les incertitudes auxquelles font face les individus concernant leur niveau de santé et particulièrement lorsqu'ils doivent déterminer le retour sur investissement en santé préventive. Les tenants du *Health Beliefs Model* ([Becker and Maiman 1975](#)) identifient un autre biais interférant dans la santé préventive : la perception subjective. La perception de son niveau de santé est subjective et peut être biaisée par de fausses croyances ([Delavande et al. 2011](#), [Delavande and Kohler 2012](#), [Chinkhumba et al. 2014](#)). Ainsi, [Kerwin \(2018\)](#) montre que les individus qui sur-estiment le risque de contracter le VIH ont tendance à engager des comportements fatalistes et à avoir des comportements sexuels plus à risque. Une fois que les fausses croyances sont corrigées, ils adoptent un comportement sexuel moins risqué.

La littérature montre que l'information est l'un des principaux vecteurs qui limitent l'impact des biais comportementaux sur la santé préventive, bien que ce domaine mérite de nouvelles recherches. Ainsi, les effets de l'information sur le comportement sexuel ou les infections aux vers parasites restent ambigus ([Kremer and Miguel 2007](#), [Dupas 2011a](#)). L'effet de l'information varie en fonction

de différents paramètres, tels que la capacité du destinataire à analyser cette information, l'identité de la personne qui transmet l'information, le moment de transmission de l'information ou encore le contenu de cette information (Dupas et al. 2018). Par exemple, de Walque (2007) souligne l'importance de l'éducation dans l'analyse des informations à propos du VIH. La recherche doit encore explorer les déterminants des effets hétérogènes des campagnes de santé. Une des hypothèses serait que les biais comportementaux apparaissent simultanément à la réception de l'information (Kremer et al. 2019). Cette hypothèse est explorée empiriquement dans le Chapitre 1 qui met en évidence le rôle de la stigmatisation dans la décision de dépistage, après des campagnes de prévention contre le VIH.

Certaines caractéristiques socio-démographiques sont corrélées aux biais comportementaux, comme l'âge. Cropper (1977) montre que les investissements faits tard dans la vie apportent un retour sur investissement sur une période plus courte que les investissements faits plus tôt, à condition la condition que le niveau de santé soit totalement indépendant de la probabilité de décès. Les déterminants socio-démographiques interagissent avec les déterminants biologiques et comportementaux dans certaines maladies chroniques, comme l'obésité, qui peuvent se transmettre des adultes aux enfants (Djemaï et al. 2019). Ainsi, le Chapitre 3 interroge l'utilisation de l'outil fiscal comme moyen de créer un choc in-utero pour changer le comportement de consommation de la mère et l'obésité des enfants.

Certains biais sont structurel aux populations dans les pays à revenu faible et intermédiaire, comme les contraintes de liquidité (Dupas and Miguel 2017). La contrainte de liquidité est un biais endogène au biais pour le présent, qui va également inhiber l'investissement en santé préventive. Les individus souffrant d'un biais pour le présent ont plus de difficulté à construire un stock de santé, ce qui réduit la demande pour les soins préventifs. D'autres biais, comme l'absence de confiance, trouvent leurs racines dans l'histoire contemporaine. Lowes and Montero (2021) montrent que les campagnes de vaccination dramatiques réalisées durant la colonisation en Afrique Centrale Française sont la cause de la méfiance à l'égard de la médecine, hypothéquant l'efficacité de programmes de santé portés par la Banque Mondiale des années après, ou la vaccination contre la Covid-19 (Solís Arce et al. 2021). De même, Archibong and Annan (2021) montrent que les campagnes de vaccination menées par une entreprise pharmaceutique américaine dans le nord du Nigéria, ont augmenté l'hésitation vaccinale dans les régions qui ont été touchées par la mort d'enfants consécutive à cette campagne.

Néanmoins, certains sous-investissements en santé préventive peuvent trouver des

explications dans l'économie comportementale du développement, notamment pour les populations à risque (Dupas and Miguel 2017). La nouvelle littérature sur les biais comportementaux dans l'investissement en santé préventive de populations à risque appelle à de nouvelles recherches. Quaife et al. (2018) montre que l'introduction de la PrEP aux travailleuses du sexe pourrait générer un comportement de compensation des risques, réduisant ainsi l'efficacité du médicament dans la lutte contre le VIH. Les résultats sont basés sur une expérimentation de choix discret, ce qui exclut une analyse de l'effet du traitement à travers le temps. Le Chapitre 2 offre une nouvelle analyse dans l'introduction de la PrEP sur le marché du sexe, montrant que la non adhésion des travailleuses du sexe à la PrEP peut s'expliquer rationnellement par le niveau de risque dans le comportement sexuel.

## 5 Contributions de cette thèse

Cette thèse fait des contributions empiriques (Chapitres 1 à 4), théoriques (Chapitre 2), méthodologiques (Chapitres 1 à 4) et en termes de recommandations politiques (Chapitres 1 à 4). Cette section présente un résumé détaillé de chaque chapitre ainsi que leur contribution.

### Chapitre 1

**Le Chapitre 1 montre que l'efficacité de certaines de politiques publiques préventives peuvent être limitées par des externalités que sont des biais comportementaux. Précisément, être exposé à un programme de prévention VIH n'a pas augmenté le dépistage au Malawi, notamment à cause de la hausse de la stigmatisation dans les zones exposées auxdits programmes.**

Ce premier chapitre s'intéresse à l'efficacité des programmes de prévention contre le VIH, financés par l'aide internationale, dans le cas du Malawi entre 2000 et 2016. Le Malawi est dépendant de l'aide internationale pour financer les programmes VIH, et récemment, la prévention est devenu l'un des postes principaux de financement. Ces programmes diffusent de l'information pour encourager les individus à adopter des comportements préventifs, comme réduire les rapports sexuels à risque ou augmenter le dépistage (Delavande et al. 2014a, Derksen et al. 2021, Kerwin 2018). Néanmoins, les programmes de prévention VIH peuvent aggraver des biais comportementaux si les individus ne sont pas capables d'analyser l'information. En d'autres termes, différents biais peuvent se développer entre le temps de diffusion de l'information et le temps où l'individu se fait dépister.

Ce chapitre utilise les quatre vagues d'Enquêtes Ménage et Santé entre 2000 et 2016 pour mesurer le dépistage. Il s'appuie également sur les bases de données AidData et du Ministère des Finances du Malawi pour la géolocalisation des programmes de prévention. La stratégie d'identification tire parti de la variation temporelle et géographique de l'implémentation des programmes pour estimer leur impact sur la décision de dépistage.

En conclusion, l'exposition à un programme de prévention n'a pas eu d'effet sur le dépistage entre 2000 et 2016 et que ce résultat est robuste à différents tests. Je montre que l'effet des campagnes de prévention changent à travers le temps. Entre 2004 et 2010, être exposé à un programme de prévention VIH réduisait la probabilité d'être dépisté de 3 points de pourcentage. Les résultats sont consistants avec ceux de l'expérimentation aléatoire contrôlée menée par [Yang et al. \(2022\)](#). Les auteurs trouvent qu'une campagne de prévention VIH réduit la probabilité de se faire dépister au Mozambique.

Ce chapitre identifie les mécanismes comportementaux intervenant dans la décision de dépistage après la diffusion d'une information préventive. Les individus exposés à un programme de prévention VIH n'ont pas plus de connaissances sur le VIH, cependant, ils ont une plus forte probabilité d'adopter des attitudes négatives vis-à-vis des individus séropositifs.

Ces mécanismes pourront être analysés plus en profondeur en collectant de nouvelles données sur le contexte de l'exposition aux programmes de prévention VIH - qui, comment et vers qui l'information est dirigée. Ce chapitre suggère que l'information peut engendrer de la stigmatisation, mais d'autres biais peuvent être en jeu et ne sont pas observés ici. Ainsi, l'analyse d'hétérogénéité montre que les hommes vont significativement moins se dépister que les femmes. Ce décalage peut s'expliquer comme une externalité négative des politiques de dépistage obligatoire des femmes enceintes. Ce sujet mérite de nouvelles recherches.

Au terme ce chapitre, on peut se demander si les bailleurs internationaux et les décideurs publics doivent intégrer les biais comportementaux dans la définition des politiques préventives. Cette proposition a été faite récemment dans les conclusions de [Quaife et al. \(2018\)](#), relatives à la diffusion de la PrEP. Etant donné que cela sous entend que les travailleuses du sexe bénéficiaires ont un biais comportemental, j'ai souhaité poursuivre ma recherche pour comprendre la rationalité dans l'adoption d'un comportement préventif, avec le Chapitre 2.

## Chapitre 2

**Le Chapitre 2 propose un nouveau modèle de choix discret pour représenter le comportement d'adhésion à un traitement préventif VIH. Ce nouveau modèle intègre le comportement sexuel à risque comme paramètre. Empiriquement, ce chapitre montre l'importance d'intégrer l'hétérogénéité des analyses coût-bénéfice dans la décision d'adhérer à un traitement préventif. Précisément, les travailleuses du sexe ont une plus forte probabilité d'adhérer à un traitement préventif contre le VIH (la PrEP) lorsque le nombre de rapports sexuels (réalisés dans le cadre professionnel) augmente, même en contrôlant pour le biais d'endogénéité et le comportement de compensation des risques.**

Ce chapitre s'intéresse à l'adoption d'un médicament préventif contre le VIH, la PrEP, par les travailleuses du sexe. Depuis 2015, l'OMS encourage les pays à donner accès à ce médicament aux populations à risque, notamment les travailleuses du sexe. Des récents travaux en économie de la santé s'intéressent à l'impact de ce médicament sur le comportement sexuel des travailleuses du sexe. L'efficacité médicale de la PrEP est remise en cause par le fait que les travailleuses du sexe puissent adopter un comportement de compensation des risques. Ce biais implique de prendre plus de risques sexuels parce que l'on se sait protéger par un traitement médical (Quaife et al. 2021). Ce chapitre apporte des informations complémentaires sur l'adhésion à la PrEP au sein des travailleuses du sexe. J'actualise les faits théoriques stylisés sur l'adhérence à un traitement préventif. Je teste ces faits stylisés avec une base de données longitudinales qui fut collectée entre Novembre 2019 et Avril 2021 à San Pedro (Côte d'Ivoire) dans le cadre du projet PRINCESSE ANRS 12381.

Le modèle théorique est adapté du modèle d'adhésion proposé par Lamiraud and Geoffard (2007), selon lequel un individu adhère à un médicament lorsque les bénéfices du médicament excède ses coûts. Les bénéfices sont mesurés par l'impact positif du traitement sur la santé, et les coûts sont mesurés par les effets négatifs du traitement sur le bien être. J'adapte ce modèle aux travailleuses du sexe et à l'adhésion à la PrEP. J'intègre le fait que le risque d'être infecté dans le contexte de l'activité sexuelle professionnelle fait varier les bénéfices de l'adhérence à un traitement préventif. Je trouve que le risque sexuel est positivement corrélé à l'adhérence à un traitement préventif, suggérant des comportements de santé rationnels. Plus une travailleuse du sexe prend des risques, plus elle adhère au traitement.

Dans un second temps, je teste les faits stylisés. La principale hypothèse

pourrait être empiriquement biaisée par la causalité inverse entre l'adhérence au traitement et la prise de risque dans le comportement sexuel, précisément à cause du comportement de compensation des risques. J'utilise un modèle en équations simultanées avec une stratégie Mundlak pour contrôler ce biais. Le risque sexuel est mesuré par le nombre de clients tandis que l'adhérence est mesurée par l'attrition observée dans le programme PRINCESSE.

Ce chapitre apporte plusieurs contributions empiriques. D'abord, il présente une nouvelle base de données uniques sur une population à risque peu étudiée. La base de données longitudinale permet d'illustrer un déclin rapide de l'adhésion à la PrEP, avec un taux de rétention qui chute à 20% au bout d'un an et demi. Le Chapitre identifie les variables invariantes dans le temps qui déterminent ce déclin (le niveau d'éducation, l'âge et le fait de travailler principalement comme une travailleuse du sexe). Ensuite, les résultats montrent que chaque client additionnel réduit la probabilité d'arrêter le traitement. En d'autres termes, plus une travailleuse du sexe à des rapports dans le cadre professionnel, moins elle abandonne son traitement. De nouvelles analyses statistiques permettront d'établir le rôle des addictions et de la santé psychologique dans l'adhésion au traitement.

Les chapitres 1 et 2 se concentrent sur la santé préventive pour le VIH, une maladie infectieuse progressivement considérée comme une maladie chronique. Les maladies chroniques sont la principale cause de décès sur le continent Africain. Le troisième chapitre s'intéresse à l'impact d'une politique publique qui cible un comportement de santé nutritionnel malsain et probablement lié à l'effet de rareté.

### Chapitre 3

**Le Chapitre 3 analyse l'impact de la taxe sur les boissons sucrées comme un choc in-utero sur la santé des enfants. Les résultats montrent qu'en moyenne, la taxe n'a pas d'impact sur l'obésité ou le risque de surpoids. Cependant, cette politique doit être associée à d'autres politiques préventives pour qu'elle puisse avoir un effet significatif sur l'Indice de Masse Corporelle (IMC) des enfants.**

Ce chapitre s'intéresse à l'efficacité d'une taxe adoptée pour augmenter le prix des boissons sucrées, appelée également "*sin tax*" au Mexique.

La consommation de boissons sucrées est associée à des maladies comme l'obésité ou les maladies cardiovasculaires. Au Mexique, les boissons sucrées représentent

12.5% du total énergétique quotidien. Le taux d'obésité est de 30% chez les adultes, 26% chez les enfants âgés de 4 à 10 ans, et 17% chez les enfants de moins de 4 ans. Les comportements nutritionnels, notamment la consommation de sucre, sont un des facteurs de ces maladies. Certaines politiques publiques tentent de réduire leur impact sur la santé publique. Les "sin tax" ont été adoptées dans 54 pays, y compris le Mexique, qui a mis en place une taxe de 10% sur les boissons sucrées au 1er Janvier 2014. Or, un an après sa mise en oeuvre, cette taxe a eu des externalités négatives sur le taux de diarrhée dans les régions avec un faible accès à l'eau. Ce chapitre évalue l'impact que cette taxe aurait eu in-utero sur la santé des enfants, en observant les effets hétérogènes sur les familles ayant un faible accès l'eau.

L'étude utilise la base de données de l'Institut National des Statistiques et de la Géographie du Mexique (INEGI). La variation des prix est mesurée avec la base de données collectée des distributeurs pour estimer l'indice des prix à la consommation. La santé des enfants (taille, poids, IMC, surpoids, et obésité) est mesurée par les variables provenant de quatre vagues de l'enquête ménage ENSANUT (2012, 2016, 2018, 2020).

Deux stratégies empiriques sont utilisées pour mesurer l'effet de la taxe. La première stratégie tire parti de la variation temporelle et géographique des prix pour définir l'exposition des enfants nés après la mise en place de la taxe et dans les Etats impactés par une forte hausse des prix (supérieure à 10%). Ensuite, j'utilise un système de différence-en-différences avec des effets fixes maternels pour contrôler les variables non-observées et invariantes dans le temps, tant au niveau des familles que des Etats.

Les résultats montrent que, en moyenne, la hausse des prix des boissons sucrées induite par la taxe diminue la taille des enfants mais n'a pas d'effet significatif sur le poids, l'IMC, le surpoids ou l'obésité. Les analyses des effets hétérogènes montrent qu'il y a un effet pour les famille où la mère a une activité physique ou travaille. D'autres analyses sont nécessaires pour explorer l'hypothèse selon laquelle les personnes ayant moins accès l'eau potable seraient plus impactées par cette taxe.

Au terme de cette introduction, je dois souligner que ma thèse a été marquée par deux ans de pandémie de Covid-19. La pandémie a permis l'innovation et de nouvelles collaboration en recherche, particulièrement pour prévenir de futures pandémies. Le chapitre suivant applique directement les recommandations politiques préventives pour analyser la propagation de la Covid-19 dans des pays africains.

Bien que ce chapitre n'intègre pas directement les biais comportementaux, il trouve sa place à part entière pour refléter les enjeux de l'investissement en santé préventive.

## Chapter 4

**Le Chapitre 4 prédit la propagation de la Covid-19 au Ghana, Kenya et Sénégal. Il modélise la propagation du virus en prenant en compte les caractéristiques invariantes dans le temps des pays étudiés et l'hétérogénéité du statut infectieux des individus. Ce chapitre prédit que le fait d'avoir une population jeune et une population essentiellement rurale limitera la propagation et la sévérité de la pandémie dans les trois pays étudiés.**

Ce Chapitre fut écrit au coeur du premier confinement mondial. Nous avons commencé le projet la première semaine de Mars 2020 et l'article fut publié le 5 mai 2020 dans le *British Medical Journal - Global Health*. Ce Chapitre a été écrit en collaboration avec trois autres chercheurs en économie et mathématiques Binta Zahra Diop, Marème Ngom, and John Ngan Pougué Biyong. Au moment de sa rédaction, l'objectif du chapitre était d'identifier rapidement les principaux paramètres de la diffusion de l'épidémie dans les pays en Afrique où le manque de données empêchaient de prédire la propagation du virus. Nous avons utilisé un modèle Susceptible-Infecté-Rémis avec des dynamiques vitales. Nous avons estimé trois  $\beta$  pour définir la gravité des symptômes et rappeler l'hétérogénéité dans les soins :  $\beta_{as}$  pour aucun symptôme ;  $\beta_{ms}$  pour des symptômes modérés ; et  $\beta_{ss}$  pour des symptômes graves. Nous avons ajouté trois paramètres additionnels dans le modèle : la structure des ages, l'urbanisation et les comorbidités.

Nous avons testé ce modèle en utilisant les données de la Corée du Sud, qui a été l'un des pays avec le système de contrôle du virus en temps réel le plus abouti. Pour le Ghana, le Kenya et le Sénégal, nous avons estimé la propagation du virus à partir des informations partagées quotidiennement par les autorités nationales et d'autres données en accès libre pour les paramètres socio-démographiques. Au total, nous avons utilisé neuf bases de données différentes. Nous avons trouvé que, comparé aux pays Européens, la jeunesse de la population Africaine et le taux de ruralité réduiraient les effets de l'épidémie. Bien que la jeunesse de la population puisse accroître le nombre d'infections du fait de sa forte mobilité, ces infections resteraient probablement asymptomatiques. D'autres modèles ont été publiés par la suite, donnant des résultats empiriques plus précis sur la propagation du virus au niveau national au Ghana, Kenya, Sénégal.

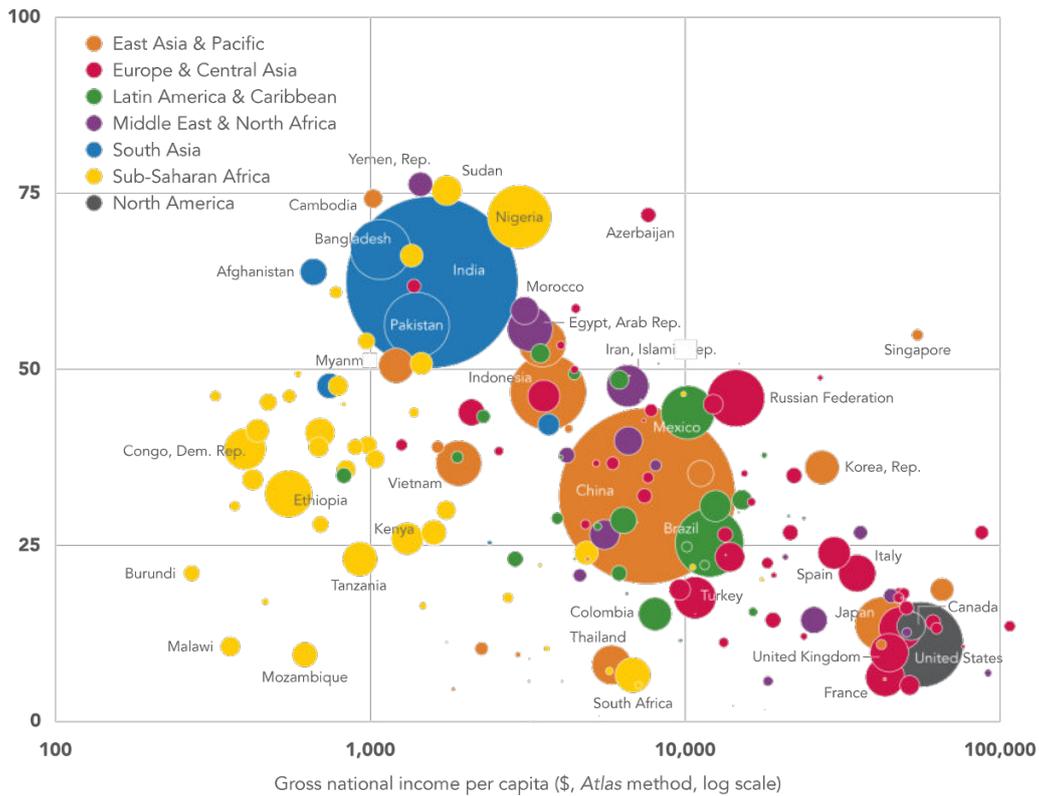
Nous avons écrit ce chapitre pour informer les décideurs publics dans une période de crise. Les résultats présentés dans ce chapitre ont été partagés avec les gouvernements du Ghana et du Sénégal, avant publication. La version de ce chapitre inclut les évolutions réelles de la propagation du virus. Pour le Ghana et le Kenya, les tendances prédites sont très proches de celles observées. Cependant, les pics des infections n'est pas aussi élevé que nos prédictions et sont arrivés un mois après les dates prédites.



## General introduction

In August 2022, the World Health Organization (WHO) announced that life expectancy extended by almost ten years in Africa between 2000 and 2019 ([World Health Organization. Regional Office for Africa 2022](#)). The WHO added that “preventing and treating infectious diseases” have been the leading drivers of this impetus. Beyond life expectancy, public policies for preventive health are key to achieving Goal 3 of the Sustainable Development Goals: “Ensure healthy lives and promote well-being for all at all ages.” Nevertheless, some regions of the world depend mainly on individual out-of-pocket expenditures to finance their healthcare systems, specifically in low and middle-income countries (LMICs) (see [Figure 1](#)).

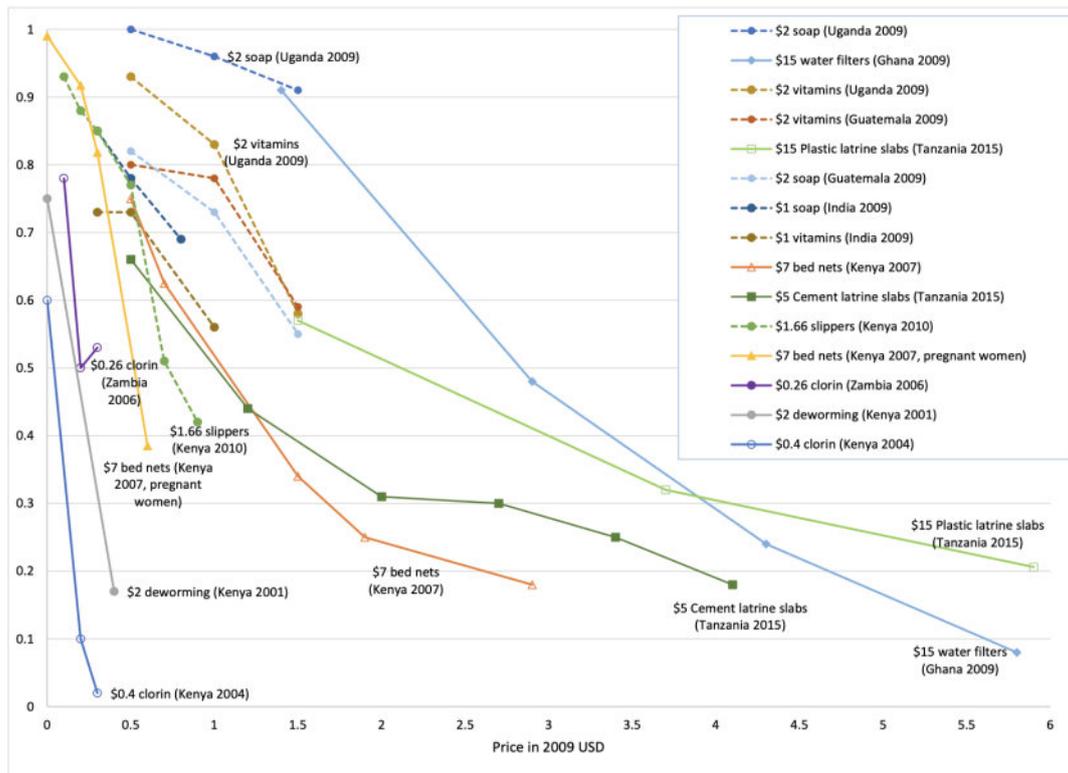
Figure 1: Out-of-pocket payments as a share of total health expenditure (2014)



Note: Out-of-pocket payments as a share of total health expenditure at national level. Circle size is proportional to population size.  
 Source: Graph designed by the World Bank Group based on WHO Global Health Expenditure database; World Bank National Accounts database; OECD National Accounts database and WDI.

In this context, financing health has become an individual responsibility and investing in preventive healthcare implies overcoming multiple direct and indirect costs. Yet, even for some free drugs, Dupas and Miguel (2017) report a substantial under-investment in preventive health in LMICs in Africa (see Figure 2).

Figure 2: Demand for preventive health products in Ghana, Kenya, Tanzania, Uganda and Zambia



Note: The graph depicts the investment in preventive health in Ghana, Kenya, Tanzania, Uganda and Zambia. The y-axis represents the share of individuals or households taking up the product. The x-axis represents the prices in USD2000.

Source: Dupas and Miguel (2017).

According to Kremer et al. (2019), canonical economics models have failed to analyze the low investment in preventive health. Thus, a growing body of literature on behavioral development economics has informed understandings of the under-investment in preventive health (Kremer et al. 2019, Dupas and Miguel 2017).

The purpose of this Dissertation is to contribute to this work by offering four chapters addressing the relationship between preventive health investment and behavioral biases. Each chapter raises a distinct research question that I answer by pulling from different empirical analyses and databases. Because they present findings in different spatial and temporal contexts, the chapters may seem distant from one another. Yet, each chapter offers a contribution to address a limitation of the chapter that precedes it and improve understanding of the links between preventive health investment and behavioral bias.

To delimit the issues of the topic, terms are defined in section 1 and the context is described in section 2. The research questions are presented in the section refmo-

tivation. A review of the literature in the section 4 will bring into perspective the contributions of this thesis, presented in the section 5.

## 1 Defining investment in preventive health and behavioral biases

The subject of this thesis could be understood in many different ways. The following section defines the terms of the topic and delineates its scope.

First, health could have two different definitions. In a restrictive sense, health is defined as “a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity” (World Health Organization 1948). Health is therefore multidimensional and subjective, as it changes according to the presence of a disease, the personal feeling of pain or the evolution of symptoms. Health refers to both physical and mental health. Although this thesis focuses on physical health, research is needed on the other dimensions of health.

In a broader sense, health goes beyond this anthropocentric perspective and talks to the community. It can be understood as global health. Koplan et al. (2009) define it as “an area of research and practice committed to applying overtly multidisciplinary, multisectoral and culturally sensitive approaches for reducing health disparities that transcend national borders.” The latest scientific achievements and the climate change invite us to consider health as a whole integrating other living beings, the ‘One Health’ (WHO 2017). In this thesis, understanding health as global health will steer each chapter to the intersection of public policy and health microeconomics. For example, Chapter 1 examines the effectiveness of foreign-funded prevention programs in promoting HIV testing in Malawi. Chapter 2 analyzes the effectiveness of a policy providing access to an HIV preventive drug (PrEP) to female sex workers in San Pedro (Côte d’Ivoire). Chapter 3 investigates the impact of a tax policy on the consumption of sugar-sweetened beverages and children’s health.

Talking about *preventive* health introduces a temporal parameter to the definition of health. Preventive health aims to “produce health” before any sickness occurs (Cohen and Henderson 1988). More formally, there are three categories of prevention that are at the core to the different chapters, namely: primary, secondary, and tertiary. Primary prevention speaks to “actions aimed at avoiding the manifestation of a disease.” Secondary prevention deals with early detection to improve the chances for positive health outcomes. Tertiary prevention involves managing the progression of symptoms to ensure the patient’s quality of life.

Chapters 2 and 3 focus primary prevention and on avoiding disease occurrence, whether by adopting a preventive treatment or a new type of diet. Chapters 1 and 4 look at secondary prevention, respectively at HIV screening and at predictions of the spread of COVID-19 in Ghana, Kenya, and Senegal. Thus, the scope of preventive healthcare is very broad, ranging from nutrition to vaccination, to sexual behavior, or, more prosaically but no less importantly, “chronic disease management” (Dupas and Miguel 2017). Although this thesis does not cover chronic disease prevention, it hopes to contribute to research in this area.

Therefore, any investment in prevention would be a benefit for health but investing in every preventive healthcare is limited by resources. Grossman (1972) characterizes health as a “durable capital good.” Each individual has a stock of health that depreciates over time and which, below a certain threshold, ends in death. It is possible to increase this stock by investing in its provision. The resources needed to invest are pecuniary and non-pecuniary. This investment can be made from an individual and microeconomic perspective or from an institutional and public policy perspective. This thesis focuses on understanding how individual and public investments intersect to promote preventive health. Chapter 1 discusses the effectiveness of public policy spending on HIV prevention in relation to the individual investment of getting tested. Similarly, Chapter 3 examines the effect of tax policy on nutritional behavior and child health. However, the investment itself is limited by the availability of resources.

From a microeconomics perspective, Figure 2 illustrates the underinvestment in preventive health even when this investment is a “high-return opportunity” (Kremer et al. 2019). For the canonical *homo economicus*, health is such a superior good that it would be irrational to consider arbitrage to invest in it (Cohen and Henderson 1988). Yet, behavioral biases could explain this underinvestment. In neo-classic microeconomics, a behavioral bias refers to the action that is considered non-optimal at a given level of knowledge, i.e., an irrational behavior. Behavioral economics, to which this thesis belongs, emphasizes that behavioral biases are “behavioral distortions that are universal features of human behavior” (Kremer et al. 2019). In other words, behavioral bias is not necessarily irrational. The literature identifies various biases like the bias for the present, the naivety, the loss aversion, social preferences, the projection bias, or false beliefs... and this thesis does not set out to define new ones.

This thesis makes an empirical contribution to the analysis of the role of behavioral biases in preventive health investment in LMICs. Specifically, the Chapter 1 suggests that stigma is an externality to the implementation of HIV-prevention

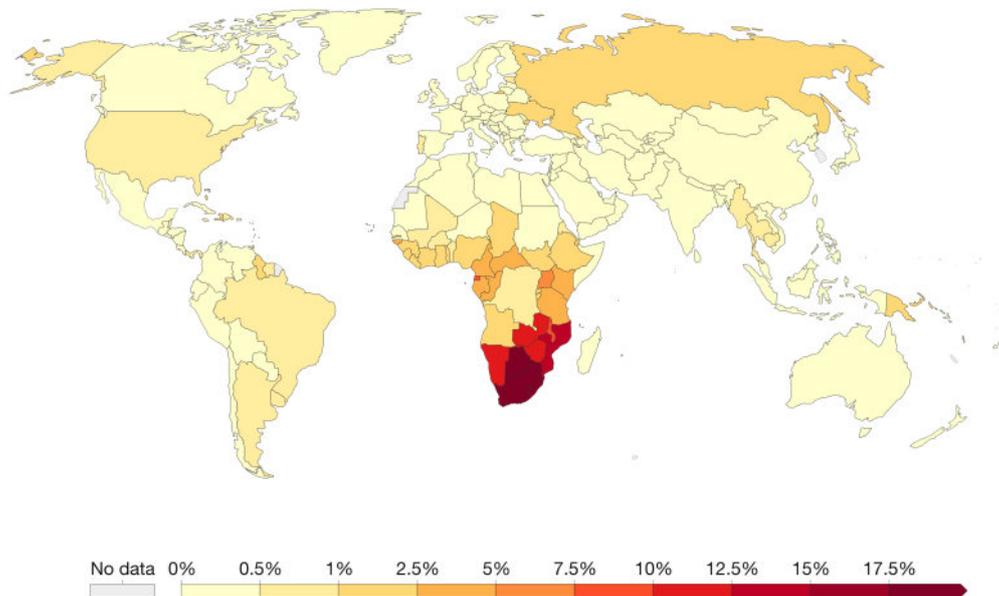
programs which interferes with HIV testing. Chapter 3 estimates the effect of a tax policy on nutritious behavior in a context of scarcity. Chapter 2 asks whether there is a behavioral bias such as the risk compensation behavior on HIV prevention among sex workers.

Finally, it should be emphasized that behavioural bias can be understood differently in public policy than in economic research. By definition, a bias is opposed to the norm, and the norm can refer to standard or average behaviour. A bias can be equated with marginal behaviour, which is not the case in behavioural economics, which presents bias as a universal behavioural distortion. Each chapter makes policy recommendations that take into account the epistemological issue of behavioral biases.

## **2 Setting the context: Low and Middle Income Countries**

This thesis focuses on preventive health and behavioral biases in low and middle-income countries and the studies are specifically conducted in African countries (Côte d'Ivoire, Ghana, Malawi, Kenya, and Senegal). With high out-of-pocket expenditure rates, the selected countries' health systems are structurally dependent on individual decisions to invest in preventive health, as shown in Figure 1. In addition, the structure of certain diseases can impact the investment in preventive health. This is why, Chapters 1 and 2 focus on HIV preventive behaviors as the countries with the highest HIV prevalence and incidence rates are located in Africa (see Figure 3).

Figure 3: Share of the population infected with HIV, in 2019



Note: This graph maps the HIV prevalence per country, calculated on men and women aged 15-49 years old.

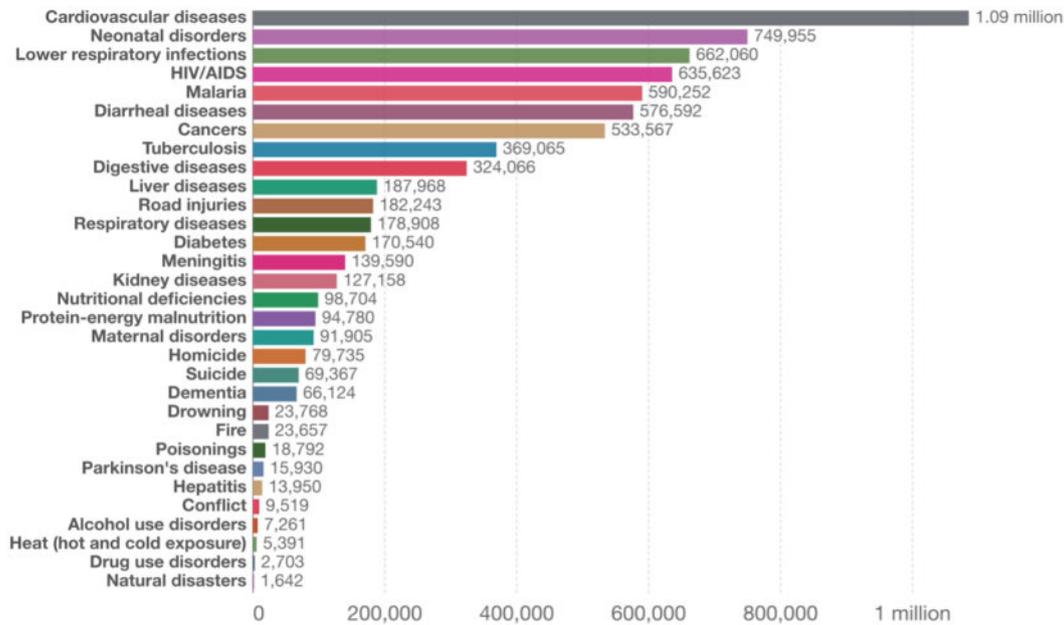
Source: [Roser and Ritchie \(2018\)](#) based on Institute for Health Metrics and Evaluation (IHME)

Similarly, Chapter 4 draws on similarities in demographic structure in different African countries' features -youth and rurality- to identify drivers of the spread of Covid-19 in Ghana, Kenya, and Senegal. In studying different countries on the African continent, it is critical to emphasize the major differences between each country. Each country remains unique and distinct although colonization defined different States with common geographical and cultural features. Consequently, certain events in health history - the spread of HIV, for example ([Oster 2005, 2012a, Anderson 2018, Djemai 2018](#)) - have crossed borders to leave a legacy of common preventive health policy parameters and behavioral biases, intentional or not.

Chapter 3 is geographically distinct in that it focuses on the impact of a sugar-sweetened-beverages tax on children's health in Mexico. This policy has been adopted in 54 countries, including four African countries only (South Africa, Mauritius, Nigeria, and Seychelles), to fight sugar consumption. Yet, diseases related to this malnutrition (cardiovascular diseases, diabete, obesity) are the main causes of death on the African continent (see Figure 4). Additionally, in 2019, 24% of overweight children under five were located on the African continent ([WHO 2022](#)). Furthermore, obesity and hypertension prevalence has had significant impact on

the COVID-19 pandemic fatality rates. Thus, the scientific contributions from the Mexican experience should be useful for countries in Africa.

Figure 4: Number of deaths by cause, African Region (WHO), 2019



Note: This chart shows the breakdown of global deaths by cause, given as the absolute number.

Source: [Ritchie and Roser \(2018\)](#) based on Institute for Health Metrics and Evaluation (IHME), Global Burden Disease.

### 3 Motivations

The behavioral development economics literature, a young field of 20 years, has called for new contributions to understanding underinvestment in preventive health ([Kremer et al. 2019](#)). Building on this literature contributes to the improvement of theoretical economic models that are necessary for understanding the demand for health care in low- and middle-income countries. [Cohen and Henderson \(1988\)](#) summarize this motivation:

*“Theoretical models are of value in that a better understanding of factors that determine the demand for prevention provides messages for public policy, but the value of the message is only as good as the value of the analysis upon which it rests. Suppose important prevention features are omitted [...]. In that case, important policy implications can be missed.”*

Although the subject has always been present in health economics, it is not well represented within the literature of development economics and at large. Since 1992, *Health Economics* has counted 1,416 publications with the term “prevention” in their publication, including 42 in the keywords and 44 in the title. The *Journal of Development Economics* has 110 publications with the term "prevention" related or not to health since 1996, including more than 10% of the publications in 2020, the year of the Covid-19 pandemic. The *American Economics Association* has only 18 health-related publications across all journals with the keywords "prevention" or "preventive". Only in Spring 2021 did the *Journal of Economic Perspectives* publish an article on health prevention ([Newhouse 2021](#)).

Investment in preventive health has always been an ongoing issue in public policy but has not been prioritized because it is costly ([Newhouse 2021](#)). Health prevention is costly because it encompasses many areas like nutrition, screening, or preventive drugs. The resources to invest in it are limited compared to other spending areas or to already resource-constrained health systems ([Cohen and Henderson 1988](#)).

Since the Covid-19 pandemic in 2020, international organizations have repositioned preventive health as a major health policy issue, particularly from a behavioral perspective.<sup>2</sup> In light of Covid-19 control policies, individual behavior has become the key to preventing the spread of the epidemic (with social distancing and handwashing, for instance). Behavioral biases, such as trust, misinformation, or misanalysis of correct information, have also been highlighted by the pandemic. This thesis has contributed to preventing Covid-19 spread in African countries. Chapter 4 was written amid the first global lockdown and it predicted the spread of the epidemic in Ghana, Kenya, and Senegal.

**Therefore, the research question of this thesis is to determine to what extent a public policy is effective when considering behavioral biases that interfere with investment in preventive health. It poses the following questions: To what extent is investment in preventive health held back by behavioral biases? To what extent can underinvestment in preventive health be rational? To what extent can a public policy impact unhealthy behavior due to a behavioral bias?**

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<sup>2</sup>See the communication of Mr. van Nieuwkoop, Global Director, Agriculture and Food Global Practice, World Bank and Mrs. Eloit, Director General of the World Organization for Animal Health.

## 4 Literature review

Preventive health investment results from a cost-benefit analysis that some individuals cannot perform because of various biases such as uncertainty or false beliefs. In 1963, [Arrow \(1963\)](#) highlighted that individuals must deal with uncertainty about their health status when estimating the return on preventive health investment. Proponents of the Health Beliefs Model ([Becker and Maiman 1975](#)) have added the subjective perceptions of the importance of taking action or the severity of an illness as one of the fundamental biases interfering with preventive health. Health perception is a subjective process that can also be biased by false beliefs ([Delavande et al. 2011](#), [Delavande and Kohler 2012](#), [Chinkhumba et al. 2014](#)). For example, [Kerwin \(2018\)](#) shows that individuals who overestimate their risk of contracting HIV tend to engage in fatalistic and sexually risky behavior. Once their false beliefs are corrected, they adopt a less risky sexual behavior.

Information is one driver to limit the impact of behavioral biases on preventive health, although the conditions for its effectiveness are debated. [Kremer and Miguel \(2007\)](#) and [Dupas \(2011a\)](#) find ambiguous effects of information interventions in avoiding worm infection or sexual behavior. The effectiveness of the information depends on different parameters, such as the recipient's ability to analyze the information, the identity of the person conveying the information, the timing of the information, and perhaps even the content ([Dupas et al. 2018](#)). For instance, [de Walque \(2007\)](#) highlights the importance of education in analyzing information received about HIV. Research has yet to explore the determinants of the heterogeneity in the effectiveness of information campaigns. One hypothesis would be that multiple behavioral biases occur simultaneously as information receipt ([Kremer et al. 2019](#)). This is explored in Chapter 1, wherein the role of stigma in the decision of testing behavior after exposure to a HIV-prevention programs.

Individual socio-demographic parameters could be the sources of behavioral bias, like the age parameter. [Cropper \(1977\)](#) demonstrates that investments made later in life bring returns over a shorter period than those made earlier, under the assumption that health is completely independent of the probability of death. Socio-demographic determinants interact with biological and behavioral determinants in some chronic diseases, such as obesity, that can be transmitted from adults to children ([Djemai et al. 2019](#)). This is why Chapter 3 investigates the use of a fiscal policy as an in-utero shock to change infant health outcomes usually resulting from mothers' health behavior.

Some biases are structural to LMICs, such as the liquidity constraint and the present bias (Dupas and Miguel 2017). Individuals with a present bias have more difficulty building up a stock (in this case of health), which reduces demand for preventive care. The liquidity constraint is a bias endogenous to the present bias, which also inhibits investment in preventive health. Other biases, such as trust, are rooted in contemporary history. Lowes and Montero (2021) show that fatal vaccination campaigns in French Central Africa during colonization left distrust in medicine, jeopardizing the goals of health programs carried out by the World Bank or stifling vaccination rates during Covid-19 (Solís Arce et al. 2021). Similarly, Archibong and Annan (2021) show that a fatal vaccination campaign run by a US pharmaceutical firm in northern Nigeria has increased vaccine hesitancy.

However, some underinvestment in preventive health can also be explained rationally, especially for at-risk populations Cropper (1977). A scarce literature focuses on specific biases in at-risk populations. Quaife et al. (2018) show that the introduction of PrEP would generate risk-compensatory behavior among sex workers, thereby reducing the effectiveness of HIV control. The results are based on a discrete choice experiment and cannot incorporate the time-variation in treatment adherence. Chapter 2 offers a new analysis on the introduction of PrEP into the sex market, showing that female sex workers' non-adherence to PrEP is related to their risk-taking in their sexual health.

## 5 Contribution of the thesis

This thesis makes empirical (Chapter 1 to 4), theoretical (Chapter 2), methodological (Chapter 1 to 4), and policy contributions (Chapter 1 to 4). This section presents each chapter's summary and its contribution.

### Chapter 1

**Chapter 1 shows that the effectiveness of some preventive public policies may be limited by behavioral bias externalities. Specifically, exposure to an HIV prevention program did not increase testing in Malawi, partly because of increased stigma in areas exposed to HIV prevention programs.**

The first chapter focuses on the effectiveness of foreign-funded HIV prevention programs in the case of Malawi between 2000 and 2016. Malawi is foreign-aid dependent to fund its HIV programs, and in recent years, prevention has become more prominent in program funding. These programs intend to disseminate infor-

mation to encourage individuals to adopt preventive behaviors such as non-risky sex or testing (Delavande et al. 2014a, Derksen et al. 2021, Kerwin 2018). However, HIV-prevention programs may negatively affect behavioral biases if individuals cannot analyze the information. In other words, different biases may interact between the time the information is disseminated and the time the individual is screened.

This chapter uses four waves of Demographic and Health Surveys from 2000 to 2016 for health outcomes, as well as the AidData and Malawi Ministry of Finance database for the HIV prevention programs' geolocation. The identification strategy is a two-way fixed-effects that takes advantage of temporal and geographic variation in the programs' implementation and observe their impact on the testing decision.

I find that, on average, exposure to HIV prevention programs had no effect on testing between 2000 and 2016, and this result is robust to various robustness tests. I show that the effectiveness of a prevention policy changes over time. Between 2004 and 2010, exposure to a prevention program was associated with a 3-percentage-point lower likelihood of getting tested. The results are consistent with the randomized control trial by Yang et al. (2022), who find that an HIV prevention campaign declined HIV testing in Mozambique.

The empirical contribution of this chapter lies in the identification of the mechanisms. First, exposure to a prevention program did not change the level of knowledge, which was already very high. Second, individuals exposed to programs were more likely to engage in negative behavior toward HIV-positive individuals. Eventually, men are less likely to be tested than women who have had children.

These mechanisms can be further analyzed by gathering more specific information about the context of exposure to HIV-prevention programs -who, how, and to whom the preventive information is directed. This chapter suggests that too many information generates stigma, but other biases likely interfere and are unobserved. Thus, heterogeneity analysis shows that men get screened significantly less than women. In addition, the gender difference may unintentionally result from mandatory screening policies for pregnant women, and it calls for further investigation.

At the end of this chapter, I wondered whether all policymakers should necessarily incorporate behavioral biases into the design of prevention policies. In the HIV literature, one of the policies where behavioral biases are most prominent is the pro-

motion of PrEP. Therefore, I was interested in whether the investment in preventive health in this context depends on rational reasoning rather than behavioral bias.

## Chapter 2

**Chapter 2 proposes a new discrete choice model to represent adherence to HIV prevention treatment. This new model incorporates risky sexual behavior as a parameter. Empirically, this chapter shows the importance of incorporating the heterogeneity of cost-benefit analyses in the decision to adhere to preventive treatment. Specifically, female sex workers are more likely to adhere to HIV prevention treatment (PrEP) as the number of sexual encounters in the workplace increases, even after controlling for endogeneity bias and risk-compensation behavior.**

The chapter focuses on adopting an HIV prevention drug, PrEP, in the sex market. Since 2015, the WHO has encouraged countries to provide access to this drug to at-risk populations, including sex workers. A scarce literature in health economics focuses on the impact of this drug on female sex workers' preventive health behavior. The medical efficacy of the treatment is proven, but according to [Quaife et al. \(2018\)](#), introducing this drug would have a negative externality on risk compensation behavior. This bias would hinder the drug's effectiveness in reducing the spread of HIV ([Quaife et al. 2021](#)). This chapter provides a complementary analysis of PrEP uptake among female sex workers. First, I update stylized theoretical facts about adherence to a preventive drug. Second, I test these stylized facts using a novel longitudinal database collected between November 2019 and April 2021 in San Pedro (Côte d'Ivoire) as part of the project PRINCESSE ANRS 12381. I conducted a qualitative survey and a pilot survey just before the Covid-19 pandemic, between December 2019 and February 2020.

The theoretical model of treatment adherence by [Lamiraud and Geoffard \(2007\)](#) shows that an individual adheres to a drug when the benefits of the drug exceed the costs. The benefits are measured by the positive impact of the treatment on health, and the costs are measured by the negative impact of the treatment's side effects on well-being. I adapt this model to female sex workers' adherence to preventive treatment. I add to the theoretical model that the benefit of adherence to preventive treatment varies according to the infectious risks taken in the context of professional sexual activity (sexual risk). I find that the sexual risk is positively associated with adherence to preventive treatment, which reveals rational behavior. The more risks a female sex worker takes, the more she is protecting herself.

In a second step, I test the stylized facts. The main hypothesis may be empirically biased by the reverse causality between adherence and sexual risk, precisely because of the risk compensation behavior. I use a simultaneous equations model to control for this bias. The sexual risk is measured by the number of clients, and the attrition to the PRINCESSE project is used as a proxy for treatment adherence. In the final specification, treatment adherence is a dichotomous variable that takes the value of 1 if the sex worker disappears from the program (i.e., non-adherence). This variable is measured several times, and outcomes are correlated over time within individuals. I use the Mundlak strategy to control for this intra-individual correlation.

This chapter makes several empirical contributions. First, the longitudinal data-base illustrates a quick decline in PrEP adherence rate, as the retention rate in PrEP care reaches less than 40% after six months. Second, the number of clients does have a significant negative impact on treatment non-adherence. In other words, the more intercourse a female sex worker has, the less likely she is to drop out of treatment.

The study will be completed by analyzing the role of addictions and psychological health in the treatment adherence.

Chapters 1 and 2 focus on preventive health for HIV, an infectious disease increasingly considered as chronic. Chronic diseases are the leading cause of death on the African continent. The third chapter focuses on the impact of a public policy targeting unhealthy behaviors.

### **Chapter 3**

**Chapter 3 estimates the impact of the sugar-sweetened beverage tax as an in-utero shock to children's health. The results show that, on average, the tax has no impact on obesity or the risk of being overweight. This policy must be combined with other preventive policies to have a significant effect on children's Body Mass Index (BMI).**

The chapter questions the effectiveness of a tax adopted to increase the prices of sugar-sweetened beverages, otherwise known as the "sin tax".

Sugar-sweetened beverages are increasingly associated with chronic diseases such as obesity or cardiovascular diseases. In Mexico, sugar-sweetened beverages

represent 12.5% of the daily energy intake. Mexico has an obesity rate of 30% in adults, 26% in children aged 4 to 10, and 17% in children under 4. Unhealthy behavior is one of the factors of these diseases, which policies try to reverse to reduce their impact on public health. The "sin tax" has been adopted in 54 countries, including Mexico. On January 1, 2014, the government of Mexico implemented a 10% excise on SSBs. However, one year after its implementation, the tax had negative externalities on the rate of diarrhea in areas with low water access. This chapter assesses whether this policy might have had an in-utero effect on children's health. It provides evidence on the heterogeneous effects on families with low water access.

The study uses the databases of the National Institute of Statistics and Geography of Mexico (INEGI). Price variation is measured with the database collected from retailers to estimate the consumer price index. Child health outcomes (height, weight, BMI, overweight, and obesity) are taken from the four waves of the ENSANUT household survey (2012, 2016, 2018, 2020).

Two empirical strategies estimate the effect of the tax. The first strategy takes advantage of temporal and geographic variation in prices to define exposure as children born after the implementation of the tax and in States impacted by a high price increase (equal to or higher than 10%). Second, I add a mother-fixed effect to control for time-invariant unobservable variables at both the family and State levels.

The results show that, on average, the tax-induced increase in sugar-sweetened beverages' price decreased children's height but did not significantly decrease weight, BMI, overweight, or obesity. In line with the literature, the effects of this tax are limited but could be stronger in combination with other policies.

Eventually, my Ph.D. was punctuated by two years of the Covid-19 pandemic. This pandemic has instilled new forms of research, particularly to prevent future pandemics. The subsequent chapter directly applies research inputs to policies to prevent the spread of Covid-19 on the African continent. Although it does not directly address behavioural biases, it is integral to this thesis.

## Chapter 4

**Chapter 4 predicts the spread of coronavirus in Ghana, Kenya, and Senegal. It models the spread of the virus by taking into account the time-invariant characteristics of the countries studied and the hetero-**

**geneity of individuals' infection status. This chapter predicted that the young rural population would limit the spread and severity of Covid-19 in Ghana, Kenya, and Senegal.**

The chapter was written amid the first global lockdown. We began this project the first week of March 2020, and it was published on May 5, 2020 on the British Medical Journal – Global Health. This chapter is a collaboration with three other researchers in economics and mathematics Binta Zahra Diop, Marème Ngom, and John Ngan Pougué Biyong. At the time of the writing, the chapter aimed at quickly identify the main parameters of the epidemic's spread in African countries where few predictions were available. The model used is the Susceptible-Infected-Recovered model with vital dynamics. We estimated three  $\beta$  for contact rates based on the heterogeneity of infection severity:  $\beta_{as}$  for no symptoms at all,  $\beta_{ms}$  for moderate symptoms, and  $\beta_{ss}$  for acute symptoms. We added three additional parameters to the model: age structure, urbanization, and comorbidities.

We tested the model with data from South Korea, which was then one of the countries with the best monitoring of the virus spread. For Ghana, Kenya, and Senegal, we monitored the virus spread information daily and added free-access data for socio-demographic parameters. In total, we used 9 different data sets. We found that, compared to estimates made for Europe's population, Africa's younger, rural population would moderate the epidemic's effects. The young population may increase the number of infections, but most of these infections will be asymptomatic or mild and will likely go undetected. Other models have subsequently been published that give more accurate empirical results regarding the impact of Covid-19 in the three study countries and other African countries.

We hope that this chapter contributed to informing policymakers. The estimates of this chapter were made available to the governments of Ghana and Senegal before publication. The chapter's updated version includes the real trend for the spread of the epidemic. For Ghana and Kenya, the predicted trajectories are very close to the actual ones. However, the peak infections did not reach the predicted number and arrived with a month's delay.



## Chapter 1

# Aid for AIDS and testing behavior: evidence from Malawi (2000-2016)

### Abstract

What is the impact of foreign aid-funded HIV-prevention programs on the testing decision? Since the 1990s, Malawi has successfully fought HIV, yet it has the 6th HIV prevalence rate (2019) and the 10th HIV incidence rate (2016) worldwide. This empirical paper studies the impact of exposure to a prevention program on screening decision. It matches foreign aid-funded HIV-prevention programs implemented between 1997 and 2017 (AidData and Ministry of Finance of Malawi) to 92,310 respondents from four Demographic and Health Survey (DHS) waves. It finds that exposure to HIV-prevention programs has not increased the likelihood of getting tested. Instead, it has decreased the likelihood of being tested by 3 percent between 2004 and 2010. This impact varies according to the intensity of exposure. The analysis of mechanisms suggests that foreign-funded HIV-prevention programs would have increased stigma without any impact on the level of knowledge about HIV, which was already high. The negative impact is stronger for men than women, encouraging further investigation into the “HIV testing burden” among couples.

**Keywords:** testing behavior, HIV, foreign aid, stigma, Malawi.

**JEL Codes:** I12, I15, F35.

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## 1 Introduction

Managing an epidemic lies on the individual's decision to get tested. Over the past 30 years, foreign aid-funded HIV prevention programs have received large financial resources to spread information and promote testing, particularly in Malawi. Malawi invested 17% of its total budget for HIV and AIDS programs in HIV prevention (i.e. USD 39,1 million in 2017). Despite a 38,6% drop in HIV prevalence rate from 2000 to 2017, Malawi is still among the countries most affected by HIV (Roser and Ritchie 2020b). According to Nunnenkamp and Öhler (2011), foreign aid failed at preventing new HIV infections. Yet, microeconomics studies assess prevention interventions (de Walque 2007) succeeded in discouraging risky sexual behaviors (Dupas et al. 2018).

This paper investigates the impact of foreign aid-funded HIV prevention programs on screening behavior. HIV prevention programs refer to programs that share information, distribute contraceptive, and encourage screening. They reduce the direct and indirect costs of information and access to drugs. They may target the general public or specific population. While prevention programs should enhance screening, other parameters could hamper their positive impact. For instance in Malawi, the selection bias in the destination of health aid (Marty et al. 2017) may limit the marginal impact on the screening decision. Plus, HIV programs may signal a high HIV prevention rate and negative spillovers on stigma, in areas where they settle.

A difference-in-differences estimates the impact of the foreign aid-funded prevention programs on testing. Like Knutsen et al. (2017), and Isaksson and Kotsadam (2018), the identification strategy takes advantage of HIV prevention programs' spatial and temporal variations to match geolocations from foreign aid-funded HIV prevention projects' and from the Malawi Demographic and Health Survey (DHS) 's respondents. The AidData database details roughly 90% of foreign aid-funded programs in Malawi between 1997 and 2012. I filled this dataset until 2017 with a dataset shared by the Ministry of Finance of Malawi. The DHS is a repeated cross-section dataset of four waves from 2000 to 2016.

Comparing exposed and non-exposed individuals would be based on the assumption that the introduction of an HIV program is not correlated to pre-existing characteristics of the location where it is to be implemented or that there are no omitted variables correlated to the aid received and the decision to be tested. This is a very strong assumption and, the fact that DHS visits different locations year after year limits the use of fixed effect areas. Nevertheless, there is always the

benefit of knowing exactly when and where programs are implemented. Individuals exposed to HIV prevention programs at the date of their interview are compared to individuals living on a site that will receive an HIV prevention program after their interview. This strategy control for unobservable time-invariant characteristics that may bias the estimates.

Results show that individuals *exposed* to a prevention program do not get more tested than those who are *To be Exposed* later. Instead, exposure to HIV prevention programs significantly decreased the likelihood of getting screened by 3 percent on average from 2004 to 2010. The main assumption is that individuals exposed at the date of the interview are comparable to those who will be exposed later on. Individuals exposed to programs early may be different than those exposed later. This threat is controlled at several stages. The initial model includes year-fixed effects to allow time variation within and across the four waves of DHS. In the sensitivity analysis, regressions are performed on sub-samples and reduced time lags between exposure and the interview.

Stigma and gender appear to be the main mechanisms for this surprising effect. Exposure to HIV prevention programs did not improve knowledge on HIV. However, the mediation analysis reveals that stigma drives 19% of the final impact. Instead, program implementation may have negative externalities by increasing fear of testing for those living in exposed areas. Eventually, the heterogeneity analysis finds that men are significantly less likely to be tested than women.

This paper contributes to understanding prevention programs' role on the fight against HIV. Previous studies explain the trends of HIV prevalence rate at the continental or national level (Oster 2005, 2012b, Greenwood et al. 2019). Other studies focus on the effect of preventive interventions on sexual behavior or HIV prevalence at the local level (Dupas 2011b, Sterck 2014, Dupas et al. 2018, Kerwin 2018). Wilson (2016) suggests that exposure to centres giving access to antiretroviral therapy increases the likelihood of being screened. Friedman (2018) reports that although ART sprawl in Kenya has reduced new HIV infections, it may have had negative spillovers on risky sexual behavior. This paper complements findings in Malawi (Thornton 2008, Godlonton et al. 2015, Delavande et al. 2014b, Kerwin 2018, Derksen et al. 2022), and gives evidence on the prevention programs' impact on testing.

Second, this paper aligns with the literature on the behavioral determinants of HIV testing. Delavande et al. (2014b) show that community intolerance towards HIV-positive people raises the social cost of seropositivity and diminishes risky

sexual behaviors. The risk of being recognized and stigmatized by their kinship also impacts HIV screening (Bond et al. 2002). In a randomized control trial (RCT) in rural Malawi, Derksen et al. (2022) finds that an adverse selection dynamic biases HIV testing rates. People who believe to be HIV-negative are more likely to get tested, while doubtful individuals avoid close HIV-testing centers for fear of meeting acquaintances and being stigmatized. They choose distant health centers to get tested, increasing transport and time costs. Additionally, the study's findings align with Yang et al. (2022). The authors conducted a RCT in Mozambique to assess the impact of a PEPFAR HIV prevention program on testing, knowledge and stigma. They find that the PEPFAR-funded program significantly and negatively affects HIV testing rates. Surprisingly, prevention interventions led to misinformation and worsens HIV-related stigmatizing attitudes. In its working paper, Kerwin (2018) highlights that some prevention programs may overestimate the likelihood of contracting HIV in Malawi. This paper contributes to understanding the prevention programs' adverse effect on stigma. Programs can have an information effect and a signal effect. The information effect increases the level of knowledge about HIV and should increase testing. Conversely, the signal effect suggests that the HIV rate is high in the area where the program is implemented. Since knowledge levels are very high in Malawi, it is more likely that the presence of the program creates apprehension about the risk of contracting HIV and discourages testing.

Eventually, this study explores the impact of foreign aid on economic development (Ndikumana and Pickbourn 2017, Marty et al. 2017, Knutsen and Kotsadam 2020, Khomba and Trew 2019) and health outcomes (Ssozi and Amlani 2015, Odokonyero et al. 2018, Kotsadam et al. 2018). This paper contributes to the discussion on the impact of foreign aid and its potential adverse effects (Easterly 2006, Deaton 2013, Dreher et al. 2017). Marty et al. (2017) find that foreign aid received by Malawi reduced malaria prevalence. Rajlakshmi and Becker (2015) find that health and water aid decreased disease severity and diarrhea incidence, respectively.

This paper proceeds as follows. Section 3 restates the context of foreign aid and HIV testing in Malawi. Section 3 and 4 describe the data and the empirical strategy, respectively. Section 5 discusses the main results with sensitivity analysis. Section 7 explores the channels through which HIV prevention programs affect testing behavior.

## 2 Context

Malawi has achieved significant progress in the fight against HIV over the past 20 years, although it has the tenth HIV prevalence rate in 2019. Preventive interventions have played an essential role in reversing the spread of HIV. Since 2000, the HIV prevention strategy has accounted for a substantial share of the budget of Malawi's Ministry of Finance. Between 2005 and 2016, the budget allocated to HIV prevention and treatment increased more than threefold, from \$66 Million to \$230 Million ([Roser and Ritchie 2020b](#)).

Foreign aid has supported the worldwide expansion of HIV prevention and testing policies, specifically in Malawi, where the HIV budget has been donor-dependent for many years. The Global Fund and PEPFAR, the two largest HIV funders, were established in 2002 and 2003, respectively, and their funding activities have strengthened HIV prevention and testing policy. In 2017/18, international aid, the Global Fund, and the Government of the United States of America represented 92% of spending on HIV in Malawi ([UNAIDS 2019](#)).

An increasing number of health centers and clinics have opened screening services. Other prevention strategies reached the most isolated people through radio, television, community health workers, or mobile clinics for HIV testing. In 2003, Malawi achieved a breakthrough by introducing the mandatory screening of pregnant women during antenatal visits as part of programs for the prevention of mother-to-child transmission of HIV (PMTCT), which has increased HIV testing among women ([WHO 2014](#)).<sup>1</sup>

The HIV prevalence rate declined from 14.83% in 2000 to 8.42% in 2019 ([Roser and Ritchie 2020b](#)). The HIV incidence rate dropped by 71% between 2000 and 2016, from 110,400 newly infected people to 31,772 newly infected people (see figure 4). In 2000, 114,591 people were sick with HIV, and 78,502 people died of HIV. In 2016, they were 103,371 sick with HIV and 24,495 dying from it (see figure [A1.1](#)). However, about 18% of women and 35% of men were never tested in 2017, and the testing rate is lower among the poorest people (Office/Malawi and ICF, 2017).

Testing is central in the fight against HIV. It increases the likelihood of being under ART treatment for seropositive people and reduces the likelihood of engaging in risky sexual behavior ([Thornton 2008](#), [Delavande and Kohler 2012](#), [Greenwood et al. 2019](#)). Being tested also encourages peers to do so ([Godlonton and Thornton](#)

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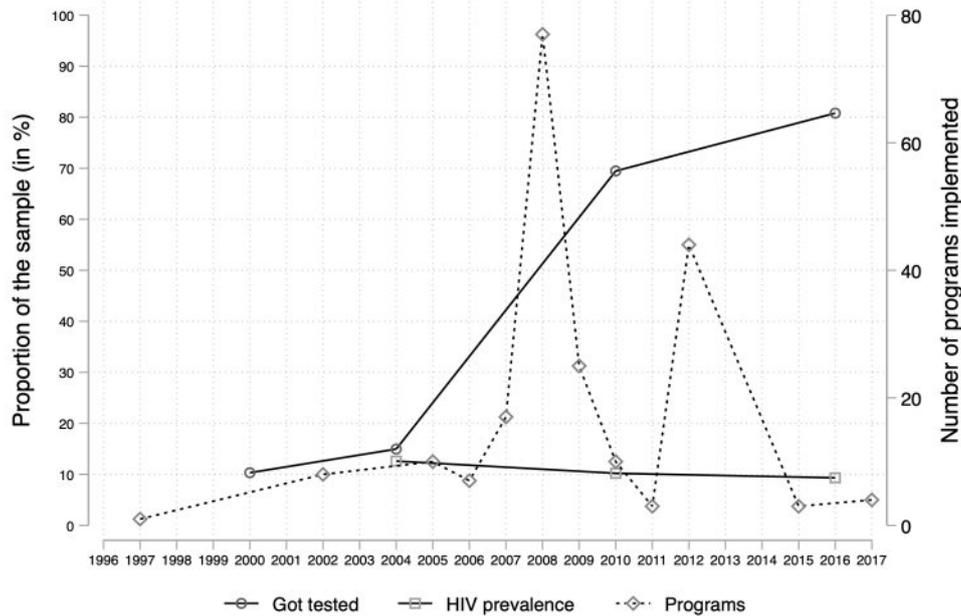
<sup>1</sup>In 2016, mother-to-child prevention prevented 13,662 infections.

2012). The government of Malawi has encouraged preventive actions to overcome some barriers to screening, such as the distance to the screening center or the waiting time for results (Ministry of Finance of Malawi, 2000, National Aids Commission of Malawi, 2011, 2015). Thus, testing is free of charge in Malawi.<sup>2</sup> One of the most supported initiatives has been anonymous testing in health centers. This strategy intended to reduce the risk of stigma but quickly showed its limitations, particularly in the follow-up of patients who tested positive. Although the government eventually revoked anonymous testing, some health centers still propose it (Bernardo et al. 2017). Additionally, the roll-out of centres giving access to antiretroviral therapy may certainly contribute to the increase of HIV testing. In a longitudinal analysis of the roll-out of the national ART program in the Tutume district of Botswana, Warwick (2006) show that the number of HIV tests significantly increased fivefold once ART became available locally. Roura et al. (2009)'s qualitative analysis highlights that access to ART can increase testing because HIV is less perceived as a fatal disease, alleviating the existing self-stigma. In the context of an RCT, Derksen et al. (2022) demonstrates that information about the effectiveness of ART is key to encouraging individuals to go for testing. However, being on ART is an external sign of recognition of the disease that can lead to new negative attitudes or stigma. The fear of being recognized and stigmatized is still one barrier to HIV testing (Derksen et al. 2022, Young and Zhu 2012). Greenwood et al. (2019) analyze HIV policies in Malawi where foreign aid has funded prevention programs. Some policies have proven to be effective. Others have had a negative impact on HIV spread because of the heterogeneity in individuals' behavior. However, there is no quantitative evidence on the impact of the roll-out of ART at national level for Malawi, to our knowledge. All in all, HIV testing and direct access to ART are key to reduce HIV prevalence and incidence Granich et al. (2009). Between 2000 and 2016, the number of people tested increased from 10% to 80% (figure 1.1) and figure A1.3 pictures a positive and concave relationship between the number of HIV prevention programs and testing at the district level.

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<sup>2</sup>There is an indirect cost to testing. The average test cost is about twice the average daily wage, whether in rural areas (Sande et al. 2018) or urban areas (Maheswaran et al. 2016).

Figure 1.1: Testing behavior, HIV prevalence and HIV-related programs (1997 to 2017)



Note: Author's graph based on AidData database and Malawi Demographic and Health Surveys. It represents HIV-related programs' trends in Malawi, testing, and HIV prevalence. The left y-axis gives the proportion of individuals who tested for HIV and the proportion of seropositive people at each survey round (2000, 2004, 2010, 2016). The HIV prevalence has only been available since 2004 when DHS questionnaires included blood sample tests. The right y-axis gives the number of HIV-related programs funded by foreign aid by the date of implementation of the agreement.

### 3 Data

This paper aims to analyze the impact of exposure to HIV prevention programs on testing behavior. It matches the geolocation of 92,310 respondents from Malawi Demographic and Health Surveys (DHS) and the location of the HIV prevention programs funded by foreign aid from the Aid Management Platform (AMP) database.

The DHS survey is sampled in two stages, representative at the national level and urban/rural level. On average, 78% of the sample are women of reproductive age (15–49 years) who were either permanent household residents or visitors who slept there the night before the survey and were eligible for participation. In one-third of the households, all men aged 15–54 years were eligible for participation if they were either permanent household residents or visitors who slept there the night before the survey. Individuals are asked about socio-demographic characteristics as well as their sexual health and behavior. Their answers are used as the main outcomes: HIV testing and HIV status (see figure 1.1). Testing is monitored with

respondents who were asked whether they already “*Got tested*”. Additionally, HIV tests were run over sub-samples of DHS interviews from 2004 to 2016 to assess respondents’ HIV status. Respondents will be split into three groups, described later in this section, for the identification strategy: *Never Exposed*, *Exposed*, and *To be Exposed*. As shown in the table [A1.2](#), the groups are balanced because the study uses four waves of the DHS: 2000, 2004, 2010, and 2016 (see table [A1.2](#)).

Table [1.1](#) presents the summary statistics of the sample per group, and table [A1.1](#) presents the balance checks between the three groups. The tables show that respondents are, on average, 28 years old, have four years of education, live mostly in rural areas (at 80%), and are married or in a couple (70%). People who are *Never Exposed* live on average 5 km from a health center, half as close as those who are *Exposed* or *To be Exposed*. Nearly 88% of the sample has had sex, with the average age of first intercourse being 14 years. In all three groups, nearly 12% of individuals reported extra-marital sex in the past year. The HIV prevalence rate is lower in the *Never Exposed* group, at 9%, compared to 13% and 14% in the *Exposed* and *To be Exposed* groups. The main difference is in the level of screening. Fifty-six percent of those who were *Never Exposed* reported having been screened, compared with 74% of those who were *Exposed* and 27% of those who were *To be Exposed*. Respondents will be geographically associated with HIV prevention programs thanks to their geolocation given by DHS.

Table 1.1: Summary statistics - By group of exposure

	(1)			Total
	Never Exposed	Exposed	To be Exposed	
<i>Demographic</i>				
Respondent's current age	28.24 (9.62)	28.80 (9.83)	27.59 (9.33)	28.24 (9.62)
Gender	0.23 (0.42)	0.23 (0.42)	0.21 (0.41)	0.22 (0.42)
Years of education	3.76 (2.64)	3.78 (2.57)	3.52 (2.64)	3.74 (2.63)
Rural	0.85 (0.35)	0.74 (0.44)	0.70 (0.46)	0.82 (0.38)
Health facilities, 10km radius	5.42 (8.84)	9.73 (15.63)	11.49 (15.98)	6.65 (11.15)
Distance to the nearest HIV-prevention program	46.34 (36.61)	3.50 (1.58)	7.73 (1.87)	41.64 (37.05)
Marital status:				
Never married	0.23 (0.42)	0.27 (0.44)	0.22 (0.41)	0.23 (0.42)
Married	0.61 (0.49)	0.55 (0.50)	0.64 (0.48)	0.61 (0.49)
Living together	0.05 (0.22)	0.06 (0.24)	0.02 (0.15)	0.05 (0.22)
Widowed	0.03 (0.16)	0.03 (0.18)	0.03 (0.17)	0.03 (0.16)
Divorced	0.04 (0.20)	0.05 (0.22)	0.05 (0.22)	0.04 (0.20)
Not living together	0.04 (0.19)	0.04 (0.19)	0.03 (0.18)	0.04 (0.19)
<i>Sexual Behavior</i>				
Already had sexual intercourse	0.88 (0.33)	0.87 (0.34)	0.89 (0.31)	0.88 (0.33)
Age of first sexual intercourse	14.47 (6.11)	14.17 (6.18)	14.60 (5.83)	14.45 (6.09)
Sex with someone else than partner last 12 months	0.11 (0.31)	0.13 (0.34)	0.12 (0.33)	0.11 (0.32)
Sex with someone else than partner last 3 intercourse	0.02 (0.12)	0.01 (0.11)	0.02 (0.15)	0.02 (0.12)
<i>HIV outcomes</i>				
Ever been tested for aids	0.56 (0.50)	0.71 (0.45)	0.24 (0.43)	0.54 (0.50)
Date of last HIV test:				
Less than 12 months	0.42 (0.49)	0.43 (0.50)	0.46 (0.50)	0.42 (0.49)
12 to 23 months	0.11 (0.31)	0.09 (0.29)	0.13 (0.34)	0.10 (0.30)
More than 24 months	0.48 (0.50)	0.48 (0.50)	0.41 (0.49)	0.47 (0.50)
HIV status - DHS test	0.09 (0.29)	0.13 (0.33)	0.14 (0.35)	0.10 (0.30)
Observations	70952	12249	10305	93506

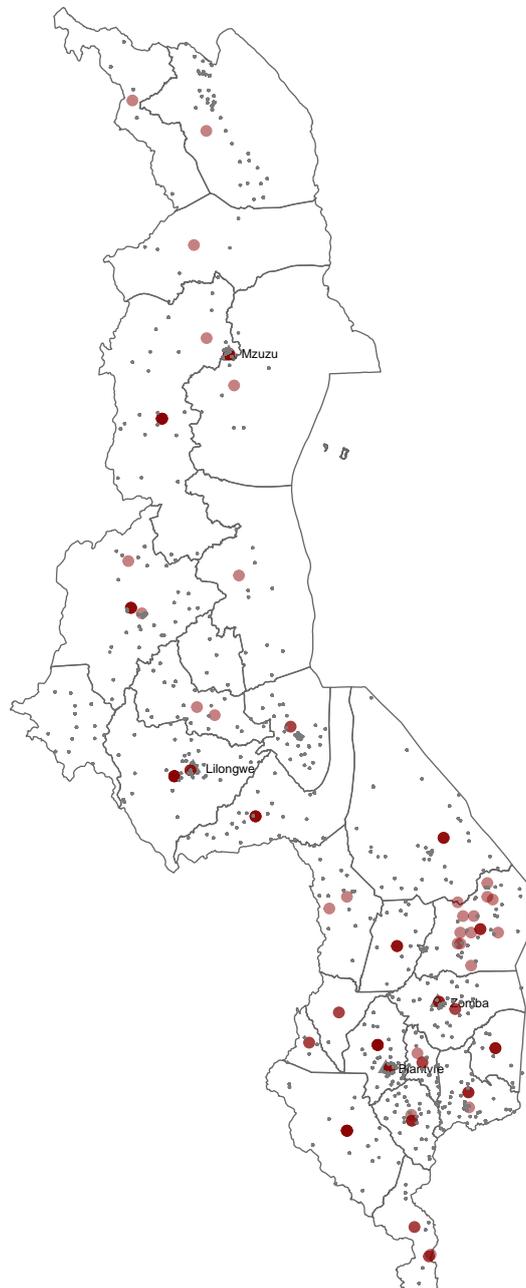
Note: Means of covariates at individual level, reported by group of exposure and for the full sample. The standard deviation is in parentheses.

Table A1.4 presents a summary of the foreign aid-funded programs monitored by the AidData’s Malawi Geocoding Project (AMP) (Peratsakis et al. 2012). This dataset tracked and reported foreign aid activities by compiling information provided by donors to the Ministry of Finance (MoF) of Malawi, such as Chinese financial transfers to Africa (Khomba and Trew 2019, Marty et al. 2017). The original dataset gathers nearly 90% of foreign-funded projects from 1997 to 2012 in various sectors such as agriculture, education, infrastructure, and health. I updated it for health programs until 2017, thanks to the AMP website and a dataset shared by the Malawi MoF. The final dataset details 561 projects in 2522 unique places: name, purpose, geolocation, funder, starting date, annual commitment, and actual disbursement. Eighty-seven projects for 304 unique locations (see figure 1.2) pursue an HIV-related goal: prevention, human resources management, scientific research, and construction of health facilities.<sup>3</sup>

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<sup>3</sup>Eventually, one can reasonably consider that this dataset captures between 70% to 80% of HIV prevention actions implemented in Malawi.

Figure 1.2: Foreign aid-funded HIV prevention programs in Malawi (1997-2017)



Note: Author's graph based on the AidData and Malawi Demographic and Health Surveys databases. Grey dots indicate the location of the survey clusters of the various DHS waves, and red shaded dots indicate the location of HIV prevention programs. The redder it is, the more programs are settled in the location.

Some HIV-related programs do not aim for prevention and may be an investment in equipment and logistics for an HIV care center or training doctors. They have an indirect impact on information and HIV prevention. Thus, I audited each project with online information, and I defined a basic index to set three categories of HIV-related projects. Each project is rated using three values: 0 for HIV-related projects with no purpose of prevention, 1 for HIV-related projects that indirectly impact prevention, and 2 for HIV-related projects with prevention as an explicit primary focus (see table A1.4). In the end, 87 are HIV-related programs, among which 29 projects with 141 unique locations strictly target HIV prevention programs. Programs implemented at the national level or without any location details are excluded. In the raw database, projects are sorted by geolocation precision, scaled from 1 (exact location) to 8 (central government projects). The sample is then restricted to programs with the exact geolocation scaled 1 to 3.<sup>4</sup> The dataset identifies 17 HIV prevention projects with 118 unique locations (see table A1.16). All in all, 32 locations were at level 1 (precise location), 2 at level 2 (up to 25km displacement), and 84 at level 3 (district level). This variation could bias the estimates. Section 6 reports estimates after a robustness test that restricts the sample to individuals *Exposed* or *To be Exposed* to programs at level 1.

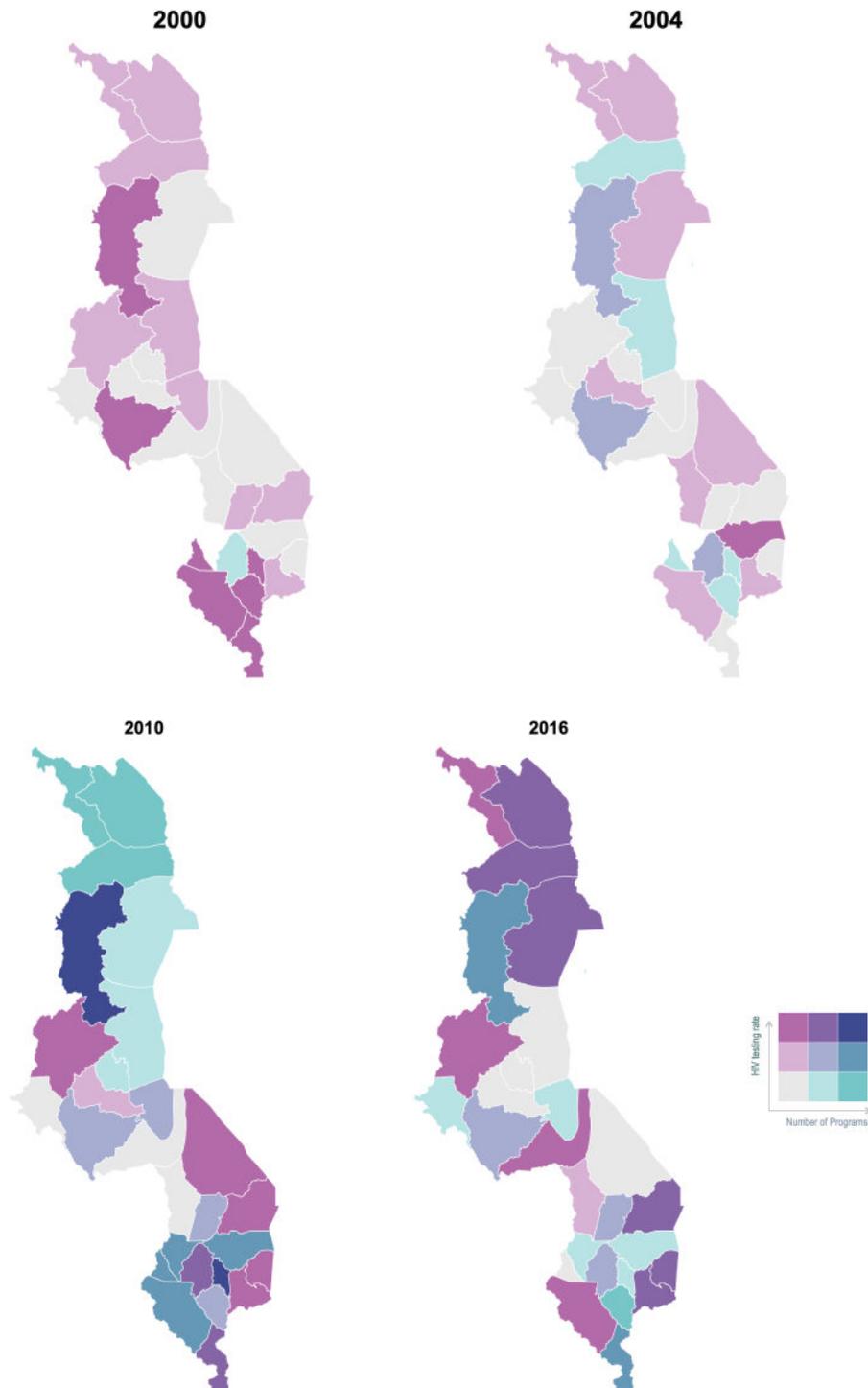
As shown in table A1.16, programs have been gradually established in 25 of Malawi's 28 districts. Looking at the figures A1.3 and A1.4, there is a positive relationship between the number of programs and the testing rate. However, the maps in figure 1.3 do not show perfect linearity. Each heat map represents the correlation between screening rates and the number of programs per 1000 inhabitants installed between  $t_0$  and  $t + 3$  (for 2000 and 2004) or  $t + 5$  (for 2010 and 2016) at the district level. The intensity of the colors represents the intensity of the correlation in the year of the survey. In the case of a perfectly linear relationship, one would observe the colors on the diagonal running from the bottom left square to the top right square exclusively. In these maps, the colors are more diverse and show less

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<sup>4</sup>Strandow et al. (2011) describes the geocoding methodology. At level 1, "The coordinates correspond to an exact location, such as a populated place or a physical structure such as a school or health center. This code may also be used for locations that join other locations to create a line such as a road, power transmission line, or railroad". At level 2, "The location is mentioned in the source as being "near", in the "area" of, or up to 25 km away from an exact location. The coordinates refer to that adjacent location". At level 3, "The location is, or is analogous to, a second-order administrative division (ADM2), such as a district, municipality or commune". The location of level 3 of Malawi is the district's capital.

linearity.

Figure 1.3: Map - Correlation between programs implemented and testing rate at district level (2000 - 2016)



Note: Author's map based on DHS and AidData databases. These maps represent the correlation between the HIV screening rate at  $t_0$  ( $t_0$  being the survey year) and the number of programs per 1000 inhabitants installed between  $t_0$  and  $t+3$  (for 2000 and 2004) or  $t+5$  (for 2010 and 2016) at the district level. The testing rate is based on the response to the question: "Have you ever been tested for HIV?" The number of programs is measured by the number of programs per 1000 inhabitants at the district level. In other words, the intensity of the colors should only be observed at the level of each map and not between maps. In the case of a perfectly linear relationship, one would observe the colors on the diagonal running from the bottom left square to the top right square.

The treatment variable is the geographical exposure to HIV prevention programs. The assumption is that individuals close to an HIV prevention program are likelier to receive information and incentives to get tested directly or indirectly. They receive it directly if the intervention directly targets them. They receive it indirectly if the intervention targets one of their kins (family, friends). The geographic matching is a proxy for exposure to HIV prevention programs. The programs' point coordinates are linked to individuals surveyed in the DHS, using the distance between the clusters' latitude and longitude of respondents to HIV prevention projects. DHS clusters are randomly moved by 2 to 5km in urban and rural areas. The median distances were 15 and 30km for urban and rural areas. In light of the literature, 15km and 30km are quite long distances that increase the risk of including non-exposed individuals in the *Exposed* group.

[Bilinski et al. \(2017\)](#) find that patients living in the Neno district (Malawi) have a higher probability of dropping their HIV treatment above an 8km distance to their health center. [Palk et al. \(2020\)](#) highlight that an increased travel distance is associated with a decreased HIV treatment initiation and retention. They also study the impact of transport costs on the retention of HIV treatment. They use a one-hour distance as the reference distance to a health facility for HIV treatment. Following them, I decided to set a one-hour walk in an urban area, which corresponds to 5km, a third of the average distance in the urban area. In rural areas, programs may use the car to cover different villages and a greater distance. I decided to set the buffer at 10km in rural areas, as it corresponds to a third of the average distance in the rural area. These cutoffs ensure a statistical power for the *Exposed* and *To be Exposed* groups and the precision of the estimates, though it is somewhat arbitrary<sup>5</sup>. Larger bandwidths are used for sensitivity analysis in section 6.

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<sup>5</sup>[Friedman \(2018\)](#) estimates the impact of Antiretroviral drug access on sexual health behavior. She justifies her choice to set the distance to the ARV center to 8km: "Eight kilometers is chosen to maximize power as it is the closest distance to the median. This generates balance between the treatment and control groups that maximizes the precision of the estimates. This distance (approximately 5 miles) is also a reasonable distance to walk for routine medical care. For robustness, the analysis is repeated using different distance cutoffs with nearly identical results. [...] The threshold of 8 km was chosen because it is near the median in order to maximize power, but - like any other distance cutoff - it is somewhat arbitrary."

## 4 Empirical strategy

The impact of exposure to HIV prevention programs is estimated thanks to a difference-in-differences strategy used in [Knutsen et al. \(2017\)](#) and [Isaksson and Kotsadam \(2018\)](#).<sup>6</sup> The spatial distribution of HIV prevention projects may be driven by local material or community support such as a health facility. [Marty et al. \(2017\)](#) show that pre-existing health infrastructures attract health projects in Malawi. One might expect that people living closer to health facilities are more demanding of and/or responsive to counseling, medical care, condoms, and/or tests for HIV because of low access costs to testing centres. The empirical strategy tries to overcome the endogeneity issue in the location of HIV prevention programs.

The empirical strategy relies on the spatial and temporal variation of the implementation of HIV prevention projects. It takes advantage of the repeated cross-section database and follows areas sampled before and after the implementation of the projects. It compares three groups of individuals: those exposed to HIV prevention programs in a 5/10km buffer before the interview (*Exposed*), those who To be Exposed to HIV prevention programs in a 5/10km buffer after the interview (*TobeExposed*), and those who are not, were not, and will not be exposed (*Never Exposed*, i.e. the control group, see table [A1.2](#)). The group *TobeExposed* controls for unobservable time-invariant characteristics that may bias the selection. The hypothesis is that areas receiving HIV prevention programs at different periods - individuals *Exposed* and *TobeExposed* - are attractive for the same determinants. Consider the following baseline regression:

$$Y_{i,d,t} = \alpha + \Gamma Exposed_{i,t} + \lambda TobeExposed_{i,t} + v_d + \delta_t + \gamma \cdot X'_{i,t} + \varepsilon_{i,d,t} \quad (1.1)$$

Where  $Y$  is a discrete variable for the testing behavior or HIV status of an individual  $i$  in a district  $d$  of year  $t$ . It equals 1 if the person got tested or is seropositive and 0 otherwise. The vector of variables  $X'$  controls individuals' characteristics, namely age, gender, marital status, wealth, religion, and education level. The covariates matrix also includes the distance to the nearest health facility

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<sup>6</sup>The estimation strategy is not so common in Economics but quite close to the strategy that uses the planned location of road infrastructure vs the actual location to correct for endogenous placement of infrastructure. See [Bird and Straub \(2014\)](#), [Donaldson \(2018\)](#), [Milsom \(2021\)](#).

(see table [A1.1](#)). The dummies *Exposed* and *TobeExposed* denote the current or future exposure to an HIV prevention program, respectively. *Exposed* variable equals 1 if a program was implemented in a 5km buffer around an individual  $i$  living in an urban area or a 10km buffer around an individual  $i$  living in a rural area, before the DHS survey. Otherwise, it takes the value 0.<sup>7</sup> The variable *TobeExposed* is equal to 1 if an HIV prevention program will settle in the 5/10km buffer around the individual  $i$  after the DHS survey is realized, and 0 otherwise. The variable *Exposed* takes precedence over *TobeExposed*. The latter cannot take the value 1 if the former does already. For instance, consider a three-year intervention implemented in an urban area from 2009 to 2012. An individual surveyed in 2004 in an urban area and living 3.6km away from the project’s location has *Exposed* = 0 and *TobeExposed* = 1. A respondent surveyed in 2010 and living 4km away has variables *Exposed* = 1 and *TobeExposed* = 0. Groups *Exposed* and *TobeExposed* are respectively compared to the control group. The control group defines individuals living further than 5 or 10 km away who are or will never be exposed. Finally, the regression has district  $v_d$  and year  $\delta_t$  fixed effects to control for the general screening trend. The final outcome is the difference between the coefficients *Exposed* and *TobeExposed*, though it does not explicitly appear in the equation. It measures the effect of exposure to an HIV prevention program.

Recent findings on the difference-in-differences show that using the two-way fixed effects (TWFE) estimator with staggered treatment adoption may bias estimates if there are heterogeneous treatment effects ([de Chaisemartin and D’Haultfœuille 2020](#), [Goodman-Bacon 2021](#), [Callaway and Sant’Anna 2021](#)). The estimator is biased if the TWFE relying on time-variation in treatment is a weighted average of two comparisons, including one using already treated units as a control group for not-yet-treated units ([Goodman-Bacon 2021](#)). The setting tackles this threat by using *never treated* individuals for the control group for the two comparisons (*Exposed* and *TobeExposed*). An additional sensitivity test supports the empirical findings in section 6. The *Exposed* and *TobeExposed* groups will be restricted to individuals exposed to HIV prevention programs within a year of the survey, reducing the time-varying effect of the treatment.

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<sup>7</sup>Migrants are not exposed if they arrived after implementing an HIV prevention program.

Following [Cameron and Miller \(2015\)](#), the error term  $\varepsilon_{i,d,t}$  is clustered at the level of the cluster survey (a village, a town, or a neighborhood, depending on whether it is an urban or rural area). It is assumed that the within-cluster correlation of the regressors is not equal to 0. The treatment status is a dummy variable based on a 5 to 10 km radius around the respondents, the latter being gathered in DHS geographical clusters. This survey criterion infers the overlapping of radius exposure.<sup>8</sup> The regression includes the DHS sampling weight.

## 5 Results

### 5.1 Main results

Table 1.2 presents the results of the linear probability model - with and without fixed effects.

Table 1.2: Exposure to HIV prevention programs

	Testing behavior		HIV status	
	Got tested (1)	(2)	Blood test result (DHS) (3)	(4)
Exposed	0.136***	0.004	-0.005	-0.004
To be exposed	-0.324***	0.028***	0.023*	0.013
Control	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Difference in differences	0.459***	-0.024***	-0.028***	-0.017
F-test: active-inactive=0	4475.449	6.817	6.573	1.779
p-value, F-test	0.00	0.01	0.01	0.18
Mean dep. var	0.543	0.543	0.102	0.102
R-squared	0.175	0.449	0.094	0.094
No. of observations	92 310	92 310	33 167	33 167

Note: \*\*\* p < .01, \*\* p < .05, \* p < .1 All estimates include controls for age, gender, marital status, wealth, rural/urban, distance to the nearest health center, and district fixed effect. Columns (1) and (3) do not include time-fixed effects, and columns (2) and (4) include year-fixed effects. All estimates are weighted using DHS sampling weights. The standard errors in parentheses are clustered at the level of the survey's clusters. The main outcome is in the bottom part of the table, named "Difference-in-Differences". It indicates the difference between the coefficients "Exposed" and "To be Exposed". The F-test and the p-value of the F-test are presented in the bottom section.

<sup>8</sup>As 40% of clusters show treatment heterogeneity, there is a weak correlation between a cluster and being exposed to an HIV prevention program.

The upper part of the table shows the impact of exposure to a prevention program. Columns (1) & (3) do not include year-fixed effects, and they align with the hypothesis that exposure to HIV prevention programs increases testing. Individuals living in areas exposed to an HIV prevention program appear to be more likely to be screened and less likely to be HIV-positive.

Columns (2) and (4) include year-fixed effects. The effect is negative but non-significant on the probability of being HIV-positive. Exposure to HIV prevention programs is positive for both those exposed and those who To be Exposed, but it is not significant for the former. However, individuals *exposed* to HIV prevention programs are not more likely to get tested, although the coefficient is positive. In contrast, individuals who *will be exposed* are 2.8 percentage points more likely to be tested than those who are never exposed.

The lower part of table 1.2 shows that the effects persist with the double difference strategy. Individuals exposed to HIV prevention programs are significantly less likely to be tested by 2.4 percentage points. Individuals who *will be exposed* tend to get more tested than those *exposed*. The results are consistent with [Yang et al. \(2022\)](#) who find a stronger and significant negative effect of 10.5 percentage points on HIV testing. The estimation is all the more surprising that there is no evidence of any impact on the HIV prevalence rate. Different explanations are further explored in section 7, including HIV knowledge and stigma.

Despite this specific identification strategy, results might be biased if foreign funders looked for places with higher HIV-test compliance year after year. Areas *to be exposed* would get a different pre-trend than areas *exposed*. Section 6 presents robustness tests.

## 5.2 Intensity of exposure

The impact of exposure varies according to the number of programs, the nature of programs, exposure before or after first sexual intercourse, or gender. This section investigates the impact heterogeneous impact of HIV prevention programs on testing behavior relative to intensity and gender.

***Intensity as the number of programs***

The first regression examined the extensive margin impact of exposure to HIV prevention programs. The concentration of HIV prevention programs may enhance exposure impact on testing behavior. The following regression includes intensity as a continuous variable measuring the number of programs (*NoPrograms*) within a 5/10km buffer. The coefficient of the double difference is now calculated from the terms  $Exposed_{i,t} * NoPrograms_{i,t}$  and  $TobeExposed_{i,t} * NoPrograms_{i,t}$ .

$$Y_{i,d,t} = \alpha + \lambda_1 Exposed_{i,t} + \lambda_2 (Exposed_{i,t} * NoPrograms_{i,t}) + \pi_1 TobeExposed_{i,t} + \pi_2 (TobeExposed_{i,t} * NoPrograms_{i,t}) + \mu NoPrograms_{i,t} + v_d + \delta_t + \gamma \cdot X'_{i,t} + \varepsilon_{i,d,t} \quad (1.2)$$

Table A1.7 shows that individuals *exposed* to HIV prevention programs are less likely to get tested than those in the control group, but the coefficient is not significant. However, people *exposed* are more likely to have been tested than those *who will be tested*, although the estimate is not significant.

***Intensity as the nature of programs***

The study focuses on HIV prevention programs. Yet, many other HIV programs range from medical training to building health centers, and these programs are complementary to fighting HIV spread. Thus, exposure to HIV programs could be more intense if it includes every type of HIV program. Model 1.1 tests the effect of exposure to any HIV programs.

Table A1.7 suggests that exposure to any HIV program reduces the negative impact of exposure to HIV prevention programs. Indeed, the coefficient (-0.3 percentage points) is negative but smaller and non-significant.

***Intensity as exposure relative to first sexual intercourse***

Finally, intensity is analyzed as exposure to HIV prevention early in sexual life. The assumption is that people will be more aware of sexual health and get more screened if they are exposed to an HIV prevention program early in their sexual life. Although there is evidence of the positive HIV prevention impact on young people

(Dupas 2011b, Dupas et al. 2018, Friedman 2018), it is not always clear how it varies according to sexual experience and which effect it has on screening.

$$Y_{i,d,t} = \alpha + \Gamma \text{Expbeforesex}_{i,t} + \lambda \text{TobeExposedbeforesex}_{i,t} + v_d + \delta_t + \gamma \cdot X'_{i,t} + \varepsilon_{i,d,t} \quad (1.3)$$

I use the age of the first sex intercourse as the threshold for sexual experience. The sample is split in three groups: (1) People *exposed* live in a 5/10km buffer and had their first sexual intercourse after the implementation of the program (*Expbeforesex*); (2) People *To be exposed before sex* live in a 5/10km buffer where the program will be implemented after the interview and after their first intercourse (*TobeExposedbeforesex*); (3) People *Never exposed* - the control group - already had their first sexual intercourse and live further than 5/10km buffer or are living with 5/10km buffer but had their first sexual intercourse before the HIV prevention program starts.

Table A1.7 estimates that individuals exposed before their first report are significantly less likely (5.2 percentage points) to have been tested than those who *will be exposed before sex*. This result is based on two assumptions. First, the variable to be *will be exposed before sex* = 1 if an individual is a virgin on the interview date and *will be exposed* after. The respondent cannot predict the age at which he will lose his virginity. This assumes that they will remain a virgin between the time of the interview and the time the program is implemented. This assumption cannot be verified. The second assumption is that exposure to the program does not delay the time of first sexual intercourse. Section 7.3 tests this hypothesis. We observe that *exposed* and *TobeExposed* individuals had their first intercourse at average ages that are not significantly different.

### 5.3 Testing behavior and gender

Since 2000, women's screening has increased faster than men's. This difference is due to free and mandatory screening of pregnant women, implemented in 2003, which does not benefit men de facto. The following model tests the gender gap by including an interaction between the treatment variable and a binary variable for

gender. It equals 1 if the respondent is a man and 0 if the respondent is a woman. First, it includes the full sample, and then it excludes women who had already been pregnant.

$$Y_{i,d,t} = \alpha + \Gamma_1 Exposed_{i,t} + \Gamma_2 (Exposed_{i,t} * Gender) + \lambda_1 TobeExposed_{i,t} + \lambda_2 (TobeExposed_{i,t} * Gender) + \phi Gender + \nu_d + \delta_t + \gamma \cdot X'_{i,t} + \varepsilon_{i,d,t} \quad (1.4)$$

Table [A1.9](#) shows that HIV prevention programs had different impacts according to gender. Exposure to a prevention program generally increased the probability of being tested, but not for men. In the top part of the table, men *exposed* are significantly 6.5 percentage points less likely to be tested after exposure to an HIV prevention program than women. As for the baseline regression, this result is compared to men who *will be exposed*. The bottom of the table presents the double difference result comparing the screening trend of men *exposed* to those who *will be exposed*. Men exposed to a prevention program are significantly 1.6 percentage points less likely to be screened after exposure than women. Column (2) supports the assumption that the gender gap may be due to free screening for pregnant women. Men are no less likely to be screened than women who have never had a pregnancy and therefore never had access to free screening. Different mechanisms may be at play and deserve to be explored later. On the one hand, this highlights that there is a gender difference in the screening cost. For women, this cost is covered either by the obligation to be screened or by the fact that it is free. On the other hand, the fact that the obligation is gendered may shift the screening responsibility to women. Indeed, although screening is individual and personal, it would be interesting to question the dynamics of screening in couples. Could it be that some people do not get tested because their spouse has had an HIV test result? One could investigate further whether the difference in testing is more marked within married couples with children than within married couples without children. The sociology literature shows the inequality in the assumption of household tasks within the couple, called “cognitive labor” ([Daminger 2019](#)) or mental load. Further investigation could focus on a “testing load”, defined as the transfer of screening responsibility from men to women.

## 6 Robustness

The sensitivity tests reveals the temporality of the effect of exposure to HIV prevention programs. The negative impact of exposure to HIV programs is limited to people exposed to programs implemented between 2004 and 2010. Plus, the effect of exposure to HIV prevention programs vanishes once the time period of exposure is reduced to one or two years around the survey.

The first threat is relative to the parallel trend assumption. The structure of the DHS database and the identification strategy are a challenge to test the pre-existing trends. Ideally, a panel database would allow to observe pre- and post-exposure variation at the individual level. However, the DHS is a repeated cross-sectional database, without a panel.

The DHS enumeration area could be thought as the substitute level to observe pre- and post-exposure variation. Unfortunately, the different DHS waves select different enumeration areas from one survey to another. Even if they would visit the same enumeration area, the identification number would not be harmonized across surveys in order to protect the anonymity of the respondents. Another possibility would be to match the geolocation across survey waves. However, DHS already alters the real geolocation between 2 and 5km, in addition to not visiting the same enumeration areas.

I therefore decide to build a quasi panel at the district level. It is the first smallest level at which DHS sampling is representative. In addition, the AidData databases give programs that are geolocated up to the district level. The choice of the district level will result in a loss of precision but remains robust for the pre-trend. As suggested, I conduct an event study using the 2000 and 2004 surveys as a baseline for districts that did not receive any programs at those dates. The event study presents the coefficient of the following equation:

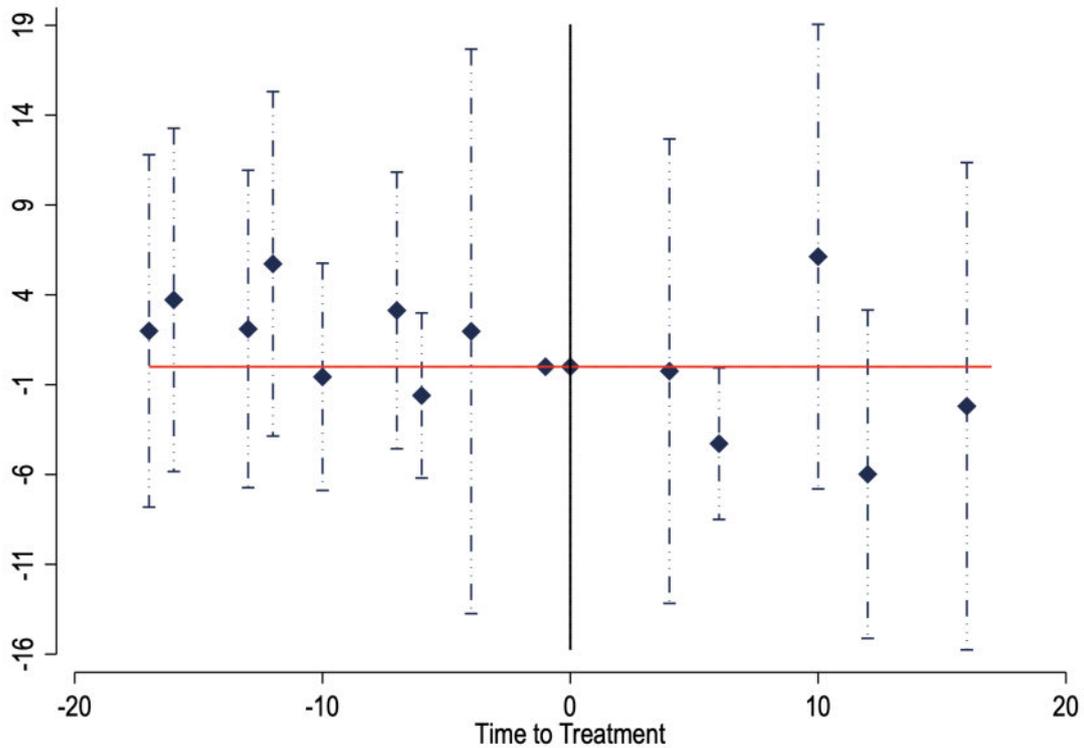
$$Y_{d,t} = v_d + \delta_t + \sum_{j=-16}^{16} \beta_j Pr_{d,t+j} + \gamma X'_{d,t} + \varepsilon_{d,t}$$

Where  $Y$  is the HIV testing rate at district level  $d$  and time  $t$ .  $X'$  is a vector of factors at district level and at time  $t$ : average years of school, average age, gender ratio, average wealth index, average distance to the first health center, proportion

of Catholics and proportion of couples (married or living together). Treatment is defined as receiving an HIV-prevention program for the first time. The specification control for year and district fixed effects.  $Pr_{d,t}$  is the event study indicator variable equal to one if an HIV-prevention programs was implemented in a district  $d$  years ago  $t$ .

Figure 1.4 graphs the HIV testing rate by year at district level, with respect to the treatment. The plotted estimates depict the differential trends in screening over up to 16 years before and after the implementation of any HIV-prevention program. There are no noticeable trends in the pre-treatment period.

Figure 1.4: Robustness - Event study for pre-trend



Note: The figure presents the estimates of  $\Sigma$  from equation 1. The treatment is defined as a district receiving an HIV prevention program for the first time. Year of HIV prevention program implementation is normalized to zero. The year before the HIV prevention program implementation is omitted. Dashed segments are 95 percent confidence intervals. The specification control for year and district fixed effects. Control variables include average years of school, average age, gender ratio, average wealth index, average distance to the first health center, proportion of Catholics and proportion of couples (married or living together).

In the second step, I use another strategy to reinforce these results at the individual level without a panel. Kuecken et al. (2021) proposes to test the parallel trends by observing the trend of the control and treated groups in population sections that are not exposed to the treatment, which is the anti-malaria campaigns.

Instead of looking at the trend over time, they look at the trend of the main outcomes across each age group. In my case, I cannot state that some individuals are more exposed than another within each group of exposure. Nevertheless, the subsample of pregnant women can be used as a counterfactual. Indeed, screening of pregnant women has been mandatory since 2003. One can therefore consider that the probability of screening relative to the number of kids should be the same whether women belong to the *Never Exposed*, *Exposed* or *TobeExposed* group. I represent the screening trend by number of births per woman and by exposure groups. I exclude the outliers and restrict the sample to women who had up to 10 kids (97% of women who ever had kids). Although the HIV testing is much lower in the *TobeExposed* group, Figure A1.5 shows parallel trends across the different groups until 7 kids.

Recent evidence in the literature question the necessity of the parallel trends test (Bilinski and Hatfield 2020, Kahn-Lang and Lang 2020, McKenzie 2020). However, table A1.1 shows imbalances in the means of control variables. The entropy balancing strategy could help to relax this assumption. The entropy balancing strategy computes a set of unit weights to balance the distribution of the covariates (Hainmueller 2012a,b). Three conditions have to hold to obtain robust results. First, the balance constraints are consistent (dimensionality of the overlap). Second, all constraints present positive weights and avoid extreme balance constraints between groups (degree of overlap). Third, the control group is large enough not to reuse the control units several times (size of the data set). The means and standard errors of the pretreatment covariates and the sample size presented in table A1.1 respect these conditions. Thus, the following variables balance the samples: years of education, age, wealth, the distance to the nearest health infrastructure, gender, religion, and the number of births for women. The entropy balancing strategy successfully balances the pretreatment covariates (see table A1.10). The results (table 1.3) show that the negative impact of exposure to HIV prevention programs (by 2.7 percentage points) is still significant at 5%.

Table 1.3: Robustness tests

	Testing behavior						
	(1) Entropy matching	(2) Control group 30km	(3) Placebo	(4) Programme FE (2000-2004)	(5) Programme FE (2004-2010)	(6) Programme FE (2010-2016)	(7) Control group To be exposed
Exposed	0.005			0.023	0.012	0.003	0.011
Exposed 10km - 30km		0.015					
To be exposed	0.032**			0.028***	0.041**	-0.007	
To be exposed 10km - 30km		0.030***					
Exposed to counterfactual projects			0.000				
To be exposed to counterfactual projects			0.000				
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Difference in differences	-0.027**	-0.015*	0.000	-0.005	-0.030**	0.010	
F-test: active-inactive=0	5.011	2.978	0.005	0.057	4.029	0.410	
p-value, F-test	0.03	0.08	0.95	0.81	0.05	0.52	
Mean dep. var	0.543	0.541	0.543	0.125	0.512	0.754	0.499
R-squared	0.384	0.452	0.448	0.065	0.347	0.239	0.424
No. of observations	92310	43916	92310	30895	44120	61415	22446

Note: \*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .1$ . This table presents coefficients of robustness tests. Column (1) displays the result of the main regression after the entropy matching reweighting. In column (2), the control group is restricted to individuals living beyond a 30km bandwidth. Column (3) individuals *exposed* and who *will be exposed* are exposed to non-health foreign aid-funded programs. Columns (4), (5), and (6) replicate the main regression and are restricted to two consecutive survey waves. All estimates include controls for age, gender, marital status, wealth, rural/urban, and distance to the nearest health center. They include year and district fixed effects. All estimates are weighted using DHS sampling weights. The standard errors in parentheses are clustered at the level of the survey's clusters. The main outcome is in the bottom part of the table, named "Difference-in-Differences". It indicates the difference between the coefficients "Exposed" and "To be Exposed". The F-test and the p-value of the F-test are presented in the bottom section.

Another threat is related to the random location of DHS clusters. It induces a risk of measurement error. In column (2) of table 1.3, the sample is restricted to compare individuals in the 10km buffer to individuals living within a distance greater than 30km to HIV prevention programs. The results are robust, although the significance power decreases at 10%. In table D3, the cut-off bandwidths are increased by 1km between 11km and 25km. The coefficients are consistent and indicate that exposure to HIV prevention programs still reduces the likelihood of being tested from 11 to 19km.

Another concern would be that exposure to HIV prevention programs captures other determinants related to the area where programs are set up. For instance, they would locate close to other foreign aid-funded programs in urban, richer, more educated, and more densely populated areas. In column (3), individuals are matched with non-health foreign aid-funded programs used as counterfactuals. The AidData database provides the interventions' coordinates in various fields, such

as agriculture or education, that are not related to HIV. Table 1.3 shows that the exposure to non-health foreign aid-funded programs does not impact testing behavior and excludes the risk of confounding variables.

Further, a potential issue is that the treatment effect may be driven by the timing of the implementation of foreign aid-funded HIV prevention programs. In the baseline results, the impact of exposure to an HIV prevention program is positive but non-significant. Programs implemented earlier may have a more significant impact - benefit by being the first program for HIV prevention. Programs implemented later would have a decreasing marginal impact in the same areas. Columns (4), (5), and (6) present the result of the regression on sub-samples of consecutive waves (2000-2004, 2004-2010, 2010-2016). For individuals *Exposed*, the results are consistently positive and non-significant. However, the estimator of the double difference is only significant between 2004 and 2010. Being exposed to HIV prevention programs decreased the probability of getting tested by 3 percentage points during this period.

The main result of the difference-in-differences could be caused by the difference between the two groups *Exposed* and *TobeExposed*. The sample is restricted to people who *will be exposed* as the group control to those who are *exposed*. The coefficient should not be significantly positive to confirm the negative relationship revealed in the main regression. Column (7) reports a positive but not-significant coefficient, supporting that individuals *exposed* do not get tested more than those who *will be exposed*.

Additionally, there is a concern about possible distribution of large time lags between interviews and program implementation for the *TobeExposed* group. An individual *Exposed* in 2008 can be surveyed in 2010 but tested in 2007. Similarly, an individual *TobeExposed* a year after the survey is not comparable to another *Exposed* four years after the survey. Table 1.4 presents a sensitivity test that reduces the sample to individuals *Exposed* or who *TobeExposed* to programs implemented within 12 months and 24 months of the interview date. I use the information in the DHS on the last test date to adapt the main outcomes. The main outcome for HIV testing equals 1 if the individual exposed the year before the

interview, declared he got tested in the previous year. Similarly for those exposed within 2 years before the survey. For the two cut-offs, individuals *Exposed* and *To be exposed* got less tested than individuals *Never Exposed*. However, the coefficient of the double difference is different from the one-year cut-off to the two-year cut-off. The former is positive while the latter is negative. These results suggest a non-linear effect of exposure to HIV prevention programs over time. The third column confirms the sign of the double difference coefficient for the one-year cut-off. The sample in this column is restricted to programs with the exact geolocation. However, it shows a different coefficient in the single differences. *Exposed* and *To be Exposed* individuals were tested more than unexposed individuals. All in all, exposure to a program fails to significantly increase the likelihood of being screened. Finally, the rate of exposure varies within the district but cannot be exactly illustrated because of some geolocations are not exact. Some projects are simply located in the district capital by default (84/118), underestimating the intra-district variability. The dataset gives 32 precise geolocations. The third column of table 1.4 presents the results of the regression on a sample reduced to individuals *Exposed* or who *To be Exposed* to programs implemented within 12 months of the interview date and for which the exact geolocation is available. The new estimates show that being exposed to HIV prevention programs within a year or two years does not impact significantly the likelihood of getting testing.

Table 1.4: Robustness tests - Time lag

	Testing behavior		
	(1)	(2)	(3)
	Cut-off 1 year	Cut-off 2 years	One-year cut-off Precision 1
Exposed within 12 months	-0.001		
To be exposed 12 months	-0.003		
Exposed within 24 months		-0.022**	
To be exposed 24 months		-0.017	
Exposed within 12 months (P1)			0.023*
To be exposed within 12 months (P1)			0.018*
Difference in differences	0.002	-0.004	0.005
F-test: active-inactive=0	0.026	0.096	0.156
p-value, F-test	0.87	0.76	0.69
Mean dep. var	0.637	0.637	0.534
R-squared	0.139	0.174	0.209
No. of observations	58.169	58.169	50.337

Note: \*\*\* p < .01, \*\*p < .05, \* p < .1 This table presents the impact of exposure to HIV prevention program on screening. The model used is similar to equation 1.1. Individuals are said *Exposed* if they live in a 5/10km buffer around a program implemented before their last test (and not the interview date). People living in a 5/10km buffer of a program starting after their testing date (or interview date by default) are in the group *To be Exposed*. The difference is that the sample is restricted to people *Exposed* and *To be Exposed* within a year (column 1) or 2 years (column 2) before and after the survey. Column 3 adds a restriction, as it includes programs with a precise localisation (Precision 1 or P1) exclusively. People living further than a 5/10km buffer around the HIV prevention program are in the control group. The date of screening is estimated based on the date of the interview and the respondent's answer to: "When was your last test: a year ago? between 12 and 24 months? more than two years ago?". I take the previous year's date for those who answered "a year ago". I take the date 18 months ago for those who answered "between 12 and 24 months". I take the date two years ago for those who answered "more than 2 years ago". All estimates include controls for age, gender, marital status, wealth, rural/urban, religion, and distance to the nearest health center. They include year and district fixed effects. All estimates are weighted using DHS sampling weights. The standard errors in parentheses are clustered at the level of the survey's clusters. The main outcome is in the bottom part of the table, named "Difference-in-Differences." It indicates the difference between the coefficients "Exposed" and "To be Exposed." The F-test and the p-value of the F-test are presented in the bottom section.

Another table proposes an additional robustness test to control for the time lags. Respondents mentioned whether the last test occurred within the last 12 months, between 12 and 24 months, or beyond 24 months<sup>9</sup>. I restrict the definition of exposure. For those *Exposed* at the interview, the main outcomes equals 1 if the last testing happened within the year. It would equal 0 if the testing happened

<sup>9</sup>I set a date 18 months ago for those who answered "between 12 and 24 months" and two years before for those who answered "more than 2 years ago".

more than 12 months ago. Individuals exposed more than a year before the interview date are not in the sample anymore. Table A1.11 reports that individuals *exposed* and *who will be exposed* are 2.8 and 3.9 more likely to get tested than those never exposed. Although the coefficient of the difference-in-differences is negative, it is not significant.

## 7 Discussion on mechanisms

HIV prevention programs impact screening through different channels. Information spreading should increase people’s knowledge about HIV and improve sexual behaviors and attitudes toward those who are - allegedly or knowingly - HIV positive. Table 1.5 presents the impact of exposure to HIV prevention on these mechanisms by replicating the main regression.

Table 1.5: Mechanisms

	(1)	(2)	(3)	(4)	(5)
	Mean	Exposed	To be exposed	Difference in Differences	<i>N</i>
<i>Knowledge</i>					
Knowledge score	6.308	0.025	0.032	-0.008	92 766
<i>Attitude</i>					
Stigma	0.285	0.003	-0.013	0.016*	92 766
<i>Sexual Behaviour</i>					
<i>All</i>					
Age of those never had intercourse	17.050	-0.024	0.098	-0.122	10 307
Age of first intercourse	19.95	0.073	-0.042	0.114	74 889
Other sexual partner (extensive margin)	0.114	0.020***	0.007	0.016***	74 889
Use condom in the last intercourse	0.098	0.009	0.004	0.005	64 688
<i>Men</i>					
Paid for sex	0.177	-0.013	0.013	-0.026*	17 414

Note: \*\*\*  $p < .01$ , \*\* $p < .05$ , \*  $p < .1$  The table presents the results of the double difference by changing the primary outcomes for variables capturing the mechanisms that would explain why exposure to HIV prevention programs might negatively impact the testing decision: Knowledge, Attitude, Sexual behavior and Gender. The estimation for sexual behavior includes controls for age, gender, wealth, rural/urban, and distance to the nearest health center. It includes year and district fixed effects. The sample is restricted to respondents who have had intercourse at least once for the sexual behavior. The standard errors, in parentheses, are clustered at the survey cluster, except for the dependent variable “Stigma (proportion per cluster)”. In column (4), The “Difference-in-Differences” indicates the difference between “Exposed” and “To be Exposed”. The F-test and the p-value of the F-test are presented in the bottom section. Columns (2) and (3) present results on the baseline sample.

## 7.1 Knowledge

Knowledge is one of the main channels through which information shared by HIV prevention interventions may impact testing behavior. It is measured by an indicator from 0 to 8 that aggregates each correct answer to a set of questions about HIV transmission (see table [A1.14](#)).

The literature has assessed that information impacts the level of knowledge ([Godlonton et al. 2015](#)), although the behavioral change following HIV information remains heterogeneous ([Gallant and Maticka-Tyndale 2004](#)). [Wilson \(2016\)](#) assesses that the impact of free counseling and testing is understated and would sharply increase testing behaviors. People exposed to HIV prevention should have a higher level of knowledge on the topic ([Paul-Ebhohimhen et al. 2008](#)). In their respective randomized control trials (RCT) in Malawi, [Kerwin \(2018\)](#) and [Derksen et al. \(2022\)](#) use information as a treatment and reveal its divergent effects on health behavior. Specifically, in [Derksen et al. \(2022\)](#), individuals receive information on the life expectancy of an HIV-positive person under ARV. The intervention increased average beliefs on the public benefit of ART and the annual testing rate in closer health facilities. [Kerwin \(2018\)](#) shows that providing information about the actual risk of HIV infection reduces the sexual activity of those with a higher HIV-infection risk estimation. The latter had a fatalistic bias, leading them to greater risky sexual activity. The dataset used in the current study does not detail the nature of the information spread. The analysis cannot assess any misinformation in the programs. Recent outcomes in the RCT run by [Yang et al. \(2022\)](#) reveal that misinformation spread in a simple exposure to an HIV prevention program heightens the stigmatizing attitude.

The level of knowledge is regressed on exposure to HIV prevention programs, using the main estimation strategy. Table [1.5](#) finds no difference in the level of knowledge between individuals *exposed, who will be exposed* or never exposed. The result is somewhat unsurprising, given that Malawi has implemented HIV education initiatives that have raised the overall knowledge to the highest ranking worldwide [Roser and Ritchie \(2020b\)](#).

## 7.2 Stigma

The second hypothesis is that exposure to an HIV prevention program may worsen the stigmatizing attitude towards - allegedly or knowingly - HIV-positive individuals. [Adeneye et al. \(2007\)](#) and [Derksen et al. \(2022\)](#) reports that stigma is one obstacle to HIV screening in their RCT in Nigeria and Malawi, respectively.

A prevention program should decrease the likelihood of stigma by increasing the level of information about the disease and its treatment. [Figure A1.6](#) does show a correlation between knowledge and stigma. However, the presence of a program may also indicate a high prevalence of HIV-positive people. Getting screened or visiting a screening center could be interpreted as the behavior of someone with risky sex life or already being HIV-positive. For instance, in [Derksen et al. \(2022\)](#), being seen regularly at the hospital for screening may be a sign of HIV infection. HIV-positive individuals are at risk of discrimination, so people prefer to choose remote health centers to be screened ([Bond et al. \(2002\)](#), Malawi Journals Project).

Stigma is regressed on exposure. The final variable is a dummy equal to 0 (no answer denoting negative attitude towards HIV) or 1 (at least one answer denoting negative attitude toward HIV). In DHS, people are asked to describe how they would act in hypothetical settings where they would meet a seropositive person. This dataset has been used by [Delavande et al. \(2014b\)](#) to measure social intolerance. Questions may suffer from social desirability bias which is controlled by the rotation in the formulation of the questions from one year to another(see [table A1.15](#)). [Table 1.5](#) shows that people exposed to HIV prevention programs are more likely to declare negative behavior, i.e. stigma, at 1.6 percentage points (significant at 10 percent). A mediation analysis estimates the treatment effect due to stigma based on the indication of [Acharya et al. \(2016\)](#) and its application by [Abebe et al. \(2021\)](#) to calculate the Average Controlled Direct Effect (ACDE). The ACDE gives ceteris paribus the treatment's direct effect. The selected mediators are fixed to give a controlled direct effect, an alternative measure of the treatment's impact. This methodology allows exploring one mechanism on the assumption. The total effect is distinct from the effect of the mediator. [Figure A1.7](#) illustrates that the impact of the exposure can be explained at 19 percent by changes in the

stigmatizing attitude. The finding should be treated with some caution given the constraints of the DHS surveys. The level of stigma is measured after the screening date. However, the results are consistent with figure A1.7, which details the analysis of this mechanism.

### 7.3 Sexual behavior

Interactions between prevention, screening, and sexual behavior are ambiguous. One might think that prevention programs increase testing and reduce risky sexual behavior. However, screening can be done before engaging in sexual intercourse, or it can be consecutive to risky sexual intercourse. HIV-information programs have proven to reduce risky sexual behavior among young girls (Dupas 2011b, Duflo et al. 2015, Dupas et al. 2018) and Friedman (2018) shows that exposure to ART would increase demand for HIV testing. As a preventive measure, the increasing screening rate would allow young women to sero-sort their potential partners. The pregnancy rate (proxy of risky sexual behavior) increases because women are aware of their partner's status and do not engage in risky intercourse.

Demonstrating the causal relationship between prevention program exposure, sexual behavior, and testing behavior is beyond the scope of this paper. However, the final section opens avenues to new analysis and encourages the collection of panel data to test these hypotheses.

#### *Age of first sexual intercourse*

Individuals exposed before their first intercourse may delay the likelihood of engaging in sex, decreasing the likelihood of being screened - since there would be no benefit to screening before sexual activity<sup>10</sup>. The regression tests the hypothesis that: *Exposure* > *Sexual behavior* > *Screening*<sup>11</sup>. Table 1.5 indicates that people *exposed* were not older than those *who will exposed* when they had their first sexual intercourse. There is no difference for those who have not yet had sexual intercourse.

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<sup>10</sup>However, 22% of those who never had sexual intercourses declare they have been tested for HIV.

<sup>11</sup>Where > means "change(s)".

### ***Sexual partners***

Individuals exposed could avoid extramarital partners to reduce the risk of contracting HIV and would therefore have less incentive to get tested. The impact chain would be: *Exposure > Sexual behavior > Screening*. However, people *exposed* may also feel more protected by HIV programs and engage in sexual intercourse with different partners. The relationship would be: *Exposure > Screening > Sexual behavior*.

DHS interviewed respondents on whether they had sexual intercourse with someone other than their partner over the past 12 months (extensive margin). Table 1.5 reports no impact on the likelihood of having another partner. However, it indicates that individuals exposed are more likely to use a condom as whether they were more careful since they are not getting tested.

### ***Paid for sex - Men***

Eventually, men exposed were significantly less likely to pay for sexual intercourse. Further investigation will clarify if they tend to reduce risky sexual intercourse because they are getting less tested.

## **8 Conclusion**

This paper proposes a quasi-experimental study to estimate the impact of foreign aid-funded HIV prevention programs on screening behavior in Malawi. It draws on two databases (Demographic and Health Survey and AidData) to show the effects of foreign aid in enhancing screening behavior. The empirical strategy takes advantage of the time and geographical variation in the implementation of the project. It matches the geolocations of DHS respondents to HIV prevention programs.

Estimates find that, on average, individuals living in areas exposed to prevention programs are 2.4 percentage points less likely to get tested. After sensitivity tests, exposure did not affect testing behavior except from 2004 to 2010, when it decreased the likelihood of getting tested by 3 percentage points. However, once the comparison of the groups is reduced to one or two years around the interview date, the negative effect is no longer significant. At best, therefore, it can be stated

that exposure to internationally funded HIV prevention programs did not have a significant positive effect on the likelihood of being tested.

The heterogeneity analysis reveals that gender affects the impact of HIV prevention programs. Men are less likely to be screened than women, except when the sample is reduced to women who never gave birth. The origin of this gender gap deserve further study, specifically because Malawi has had a policy of mandatory screening for pregnant women only since 2013.

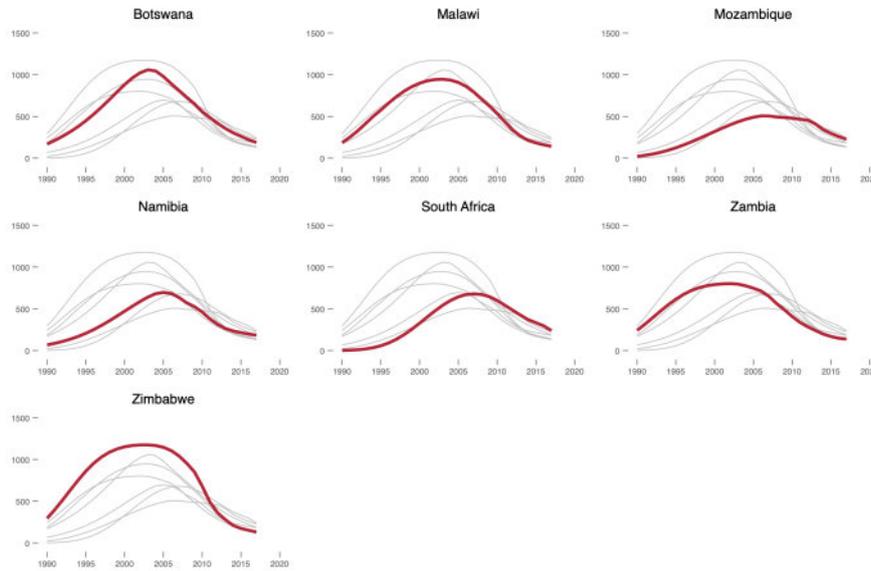
Mechanisms analysis shows behavioral spillovers of foreign aid-funded HIV prevention programs. People that have received the programs are also more likely to stigmatize others by 1.6 percentage points. However, being exposed did not increase the level of knowledge about HIV. One explanation is that there is little variation in HIV knowledge across the country. People have a high level of knowledge about HIV thanks to national investment in education for HIV. In another setting, like Mozambique, [Yang et al. \(2022\)](#) show that information disclosed may be misunderstood by those who receive it and that people are more likely to stigmatize after participating in prevention programs. However, the information disclosed by prevention programs needs to be more precisely documented in a further study, such as what was shared and to whom. The limited effect of prevention programs does not question the importance of disseminating information to encourage the adoption of preventive health behavior. Rather, these results reveal that the coordination of the funds' allocation is just as important as the microeconomic impact.

One can imagine that a randomized control trial would have been preferable to secure the experiment's internal validity. However, this choice may remain a second best choice. Randomized control trials require substantial financial expenses that would benefit from being directly invested in HIV treatment, screening or prevention programs. The first option would be a longitudinal database, that would allow to implement a more canonical two-way fixed effects to estimate the impact of foreign aid on testing. However, [de Chaisemartin and D'Haultfœuille \(2020\)](#), [Callaway and Sant'Anna \(2021\)](#), [Goodman-Bacon \(2021\)](#) highlight the risk of bias with a staggered treatment.

All in all, as new health priorities may threaten budget mobilization in the fight against HIV, accurate estimation of foreign aid effectiveness is crucial. Research could identify the channels that would explain it with more detailed data.

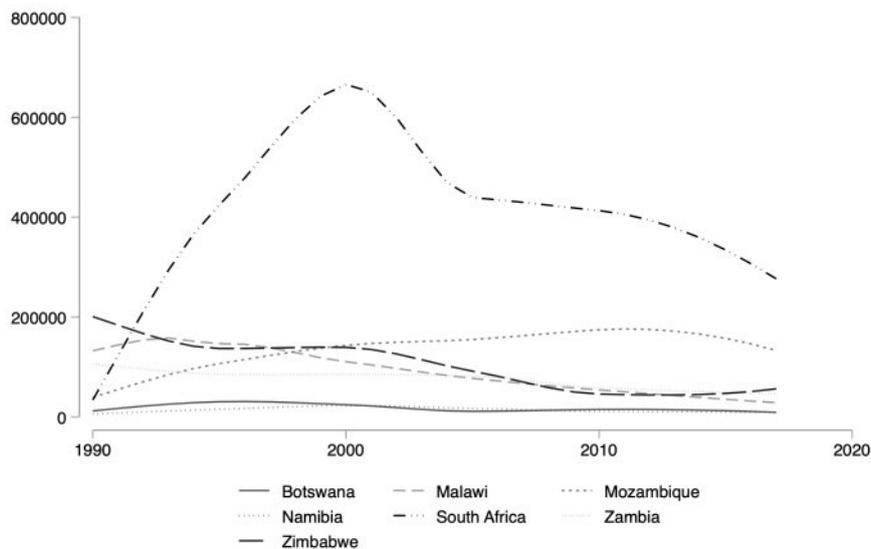
## Appendix A1. Chapter 1

Figure A1.1: HIV death rate per 100 000 in Southern African countries



Note: Author's graph from the database of [Roser and Ritchie \(2020b\)](#). The HIV death rate is the annual number of deaths from HIV per 100 000 people from 1990 to 2017. Selected countries: Botswana, Malawi, Mozambique, Namibia, South Africa, Zambia, and Zimbabwe.

Figure A1.2: HIV incidence rate per 100 000 in Southern African countries



Note: Author's graph from the database of [Roser and Ritchie \(2020b\)](#). The HIV incidence rate is the annual number of new HIV cases from 1990 to 2017. Selected countries: Botswana, Malawi, Mozambique, Namibia, South Africa, Zambia, and Zimbabwe.

Table A1.1: Balance table - Exposed, To be Exposed, Never Exposed

	Never Exposed vs. Exposed	Never Exposed vs. To be Exposed	Exposed vs. To be Exposed
<i>Demographic</i>			
Age	-0.560*** (0.094)	0.641*** (0.101)	1.201*** (0.128)
Gender	-0.005 (0.004)	0.018*** (0.004)	0.023*** (0.006)
Years of education	-0.016 (0.026)	0.239*** (0.028)	0.255*** (0.035)
Rural	0.112*** (0.004)	0.153*** (0.004)	0.041*** (0.006)
Health facilities, 10km radius	-4.317*** (0.099)	-6.074*** (0.106)	-1.757*** (0.211)
Distance to the nearest HIV-prevention program	42.842*** (0.482)	38.616*** (4.849)	-4.226*** (0.211)
Marital status:			
Never married	-0.037*** (0.004)	0.010** (0.004)	0.047*** (0.006)
Married	0.067*** (0.005)	-0.028*** (0.005)	-0.095*** (0.007)
Living together	-0.011*** (0.002)	0.028*** (0.002)	0.038*** (0.003)
Widowed	-0.007*** (0.002)	-0.003* (0.002)	0.004* (0.002)
Divorced	-0.011*** (0.002)	-0.010*** (0.002)	0.000 (0.003)
Not living together	-0.002 (0.002)	0.003 (0.002)	0.005* (0.003)
<i>Sexual Behavior</i>			
Already had sexual intercourse	0.008** (0.003)	-0.016*** (0.003)	-0.023*** (0.004)
Age of first sexual intercourse	0.302*** (0.065)	-0.131** (0.066)	-0.433*** (0.085)
Sex with someone else than partner last 12 months	-0.024*** (0.003)	-0.014*** (0.003)	0.010** (0.004)
Sex with someone else than partner last 3 intercourse	0.003** (0.001)	-0.009*** (0.001)	-0.011*** (0.002)
<i>HIV outcomes</i>			
Ever been tested for aids	-0.154*** (0.005)	0.315*** (0.005)	0.469*** (0.006)
Date of last HIV test:			
Less than 12 months	-0.015*** (0.005)	-0.044*** (0.011)	-0.029** (0.011)
12 to 23 months	0.015*** (0.003)	-0.026*** (0.007)	-0.040*** (0.007)
More than 24 months	-0.000 (0.005)	0.069*** (0.011)	0.070*** (0.011)
HIV status - DHS test	-0.033*** (0.004)	-0.046*** (0.007)	-0.013 (0.009)

Note: The table presents the t-statistics with standard error is in parentheses. The mean difference is significant if \*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .1$ .

Table A1.2: DHS composition per year

	NverExposed	xposed	Tobxposed	Total
<i>Individual level</i>				
2000	15.64	0.87	49.55	17.44
	[11 099 ]	[107 ]	[5106 ]	[16 312 ]
2004	14.78	6.74	35.40	16.00
	[10 486 ]	[825 ]	[3648 ]	[14 959 ]
2010	33.25	46.76	8.48	32.29
	[23 593 ]	[5728 ]	[874 ]	[30 195 ]
2016	36.33	45.63	6.57	34.27
	[25 774 ]	[5589 ]	[677 ]	[32 040 ]
Total	100.00	100.00	100.00	100.00
	[70 952 ]	[12 249 ]	[10 305 ]	[93 506 ]
<i>District level</i>				
	Control	xposed	Tobxposed	Total
2000	30.43	1.75	52.38	24.59
	[7 ]	[1 ]	[22 ]	[30 ]
2004	34.78	12.28	35.71	24.59
	[8 ]	[7 ]	[15 ]	[30 ]
2010	13.04	42.11	7.14	24.59
	[3 ]	[24 ]	[3 ]	[30 ]
2016	21.74	43.86	4.76	26.23
	[5 ]	[25 ]	[2 ]	[32 ]
Total	100.00	100.00	100.00	100.00
	[23 ]	[57 ]	[42 ]	[122 ]

Note: Proportion of each wave in the final sample, at individual and district levels. The number of observations is in brackets.

Sources [Office/Malawi and ICF \(2017\)](#), [NSO/Malawi and Macro \(2011\)](#), [NSO/Malawi and Macro \(2005\)](#), [Office/Malawi and Macro \(2001\)](#).

Table A1.3: Summary statistics - By year of survey

	Survey year				Total
	2000	2004	2010	2016	
<b><i>Demographic</i></b>					
Respondent's current age	28.04 (9.64)	28.10 (9.44)	28.35 (9.72)	28.30 (9.60)	28.24 (9.62)
Gender	0.19 (0.39)	0.22 (0.41)	0.24 (0.43)	0.23 (0.42)	0.22 (0.42)
Years of education	3.39 (2.72)	3.51 (2.70)	3.89 (2.63)	3.87 (2.54)	3.74 (2.63)
Rural	0.78 (0.41)	0.86 (0.35)	0.86 (0.34)	0.78 (0.41)	0.82 (0.38)
Health facilities, 10km radius	8.00 (12.74)	7.17 (10.91)	5.78 (10.71)	6.54 (10.73)	6.65 (11.15)
Distance to the nearest HIV-prevention program	86.98 (47.76)	67.22 (38.36)	31.84 (29.15)	27.84 (23.43)	41.63 (37.04)
Marital status:					
Never married	0.21 (0.40)	0.20 (0.40)	0.24 (0.43)	0.26 (0.44)	0.23 (0.42)
Married	0.67 (0.47)	0.66 (0.47)	0.57 (0.50)	0.59 (0.49)	0.61 (0.49)
Living together	0.02 (0.13)	0.04 (0.19)	0.09 (0.28)	0.04 (0.20)	0.05 (0.22)
Widowed	0.03 (0.17)	0.03 (0.17)	0.03 (0.17)	0.02 (0.15)	0.03 (0.16)
Divorced	0.04 (0.20)	0.04 (0.20)	0.04 (0.20)	0.04 (0.20)	0.04 (0.20)
Not living together	0.03 (0.17)	0.03 (0.17)	0.04 (0.19)	0.04 (0.21)	0.04 (0.19)
<b><i>Sexual Behavior</i></b>					
Already had sexual intercourse	0.90 (0.30)	0.89 (0.31)	0.86 (0.34)	0.88 (0.33)	0.88 (0.33)
Age of first sexual intercourse	14.71 (5.78)	14.73 (5.92)	14.26 (6.47)	14.34 (5.90)	14.45 (6.09)
Sex with someone else than partner last 12 months	0.12 (0.32)	0.09 (0.29)	0.10 (0.30)	0.14 (0.35)	0.11 (0.32)
Sex with someone else than partner last 3 intercourse	0.03 (0.16)	0.02 (0.14)	0.01 (0.09)	0.01 (0.12)	0.02 (0.12)
<b><i>HIV outcomes</i></b>					
Ever been tested for aids	0.10 (0.30)	0.15 (0.36)	0.69 (0.46)	0.81 (0.39)	0.54 (0.50)
Date of last HIV test:					
Less than 12 months	. (.)	0.48 (0.50)	0.39 (0.49)	0.45 (0.50)	0.42 (0.49)
12 to 23 months	. (.)	0.25 (0.43)	0.06 (0.23)	0.14 (0.35)	0.10 (0.30)
More than 24 months	. (.)	0.27 (0.45)	0.55 (0.50)	0.41 (0.49)	0.47 (0.50)
HIV status - DHS test	. (.)	0.13 (0.33)	0.10 (0.30)	0.09 (0.29)	0.10 (0.30)
Observations	16312	14959	30195	32040	93506

Note: Means of covariates at individual level, reported by year of survey and for the full sample. The standard deviation is in parentheses.

Table A1.4: Foreign aid-funded programs in Malawi (1997-2017)

Sector	Geolocation level	Number of programs	Number of unique locations
All programs	1 - 8	561	2522
All HIV-related programs	1 - 8 1 - 3	87 38	304 237
Programs of prevention for HIV	1 - 8 1 - 3	29 17	141 118

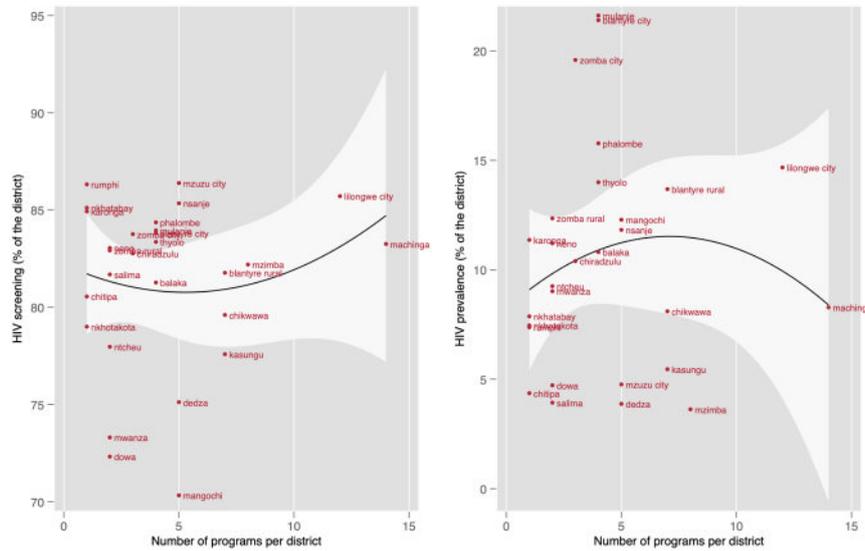
Note: [Strandow et al. \(2011\)](#) describes the geocoding methodology. Geolocation levels 1 to 3 include programs established at the district and traditional authority levels. At level 1, "The coordinates correspond to an exact location, such as a populated place or a physical structure such as a school or health center. This code may also be used for locations that join other locations to create a line, such as a road, power transmission line, or railroad". At level 2, "The location is mentioned in the source as being "near," in the "area" of, or up to 25 km from an exact location. The coordinates refer to that adjacent location". At level 3, "The location is, or is analogous to, a second-order administrative division (ADM2), such as a district, municipality or commune". The location of level 3 of Malawi is the district's capital. At level 4, "The location is, or is analogous to, a first order administrative division (ADM1), such as a province, state or governorate." At level 5, "the location can only be related to estimated coordinates, such as when a location lies between populated places; along rivers, roads and borders; more than 25 km away from a specific location; or when sources refer to parts of a country greater than ADM1 such as a National Park which spans across several provinces (e.g. Forêt Classee de Gongon in Benin)". At level 6, "The location can only be related to an independent political entity, meaning the pair of coordinates that represent a country. This includes aid that is intended for country-wide projects as well as larger areas that cannot be geo-referenced at a more precise level." At level 7, the geolocation is "unclear". "The country coordinates are entered to reflect that subcountry information is unavailable." At level 8, "the location is estimated to be a seat of an administrative division (local capital) or the national capital." All programs geolocated at a level between 4 and 8 are established at the regional or national level. All in all, 32 locations were at level 1, 2 at level 2, and 84 at level 3.

Table A1.5: Distribution of programs per year and districts

	2000	2004	2010	2016	2017	Total
Total number of programs	1	8	54	32	23	118
Number of district receiving programs	1	4	20	11	19	25

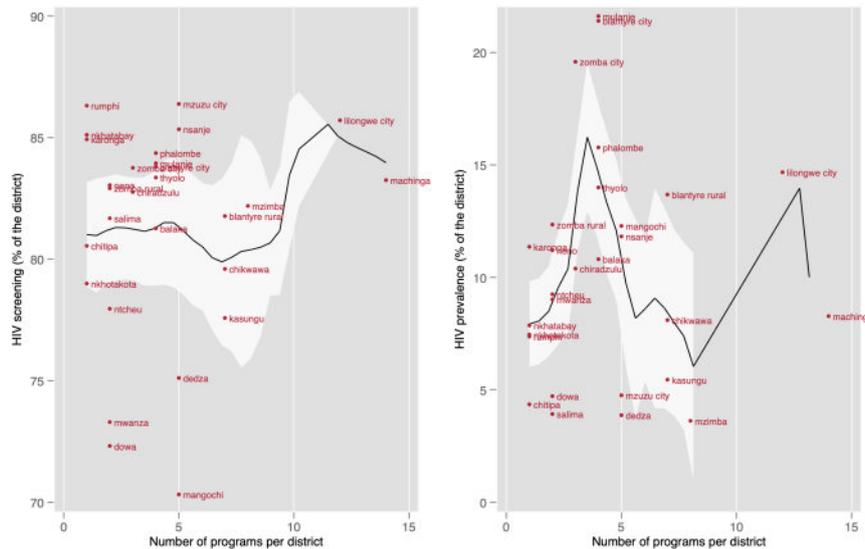
Note: The table shows the number of programs implemented at national and district level, at the mtme of the survey DHS survey from 2004 to 2016. I add those implemented in 2017. The distribution takes into account the projects' starting and ending dates. It also shows the number of districts receiving these programs per year. Malawi has 28 districts. The Northern Region includes the districts of Chitipa, Karonga, Likoma, Mzimba, Nkhata Bay, Rumphi. The Central Region includes the districts of Dedza, Dowa, Kasungu, Lilongwe, Mchinji, Nkhotakota, Ntcheu, Ntchisi, Salima. The Southern Region includes the districts of Balaka, Blantyre, Chikwawa, Chiradzulu, Machinga, Mangochi, Mulanje, Mwanza, Nsanje, Thyolo, Phalombe, Zomba, Neno. The following districts did not receive programs: Likoma, Mchinji, Ntchisi.

Figure A1.3: HIV prevention programs and testing behavior - quadratic regression (district level)



Note: The graph estimates a non-linear correlation at the district level between main outcomes and the number of HIV prevention programs implemented before the survey. The main outcomes are the ratio of people who declared already tested and the HIV prevalence rate.

Figure A1.4: HIV prevention programs and testing behavior - local polynomial regression (district level)



Note: The graph estimates a non-linear correlation at the district level between main outcomes and the number of HIV prevention programs. The main outcomes are the ratio of people who declared they already tested for HIV and the HIV prevalence rate.

Table A1.6: Exposure to HIV prevention programs - Logistic regression

	Testing behavior			HIV status		
	(1)	(2)	(3)	(4)	(5)	(6)
Distance to the nearest HIV-prevention program	-0.014***	-0.022***	-0.001*	-0.003***	0.004***	0.000
Years of school		0.125***	0.104***		0.030***	0.036***
Age		0.033***	0.030***		0.069***	0.070***
Men		-0.613***	-0.744***		-0.629***	-0.641***
Wealth		0.000***	0.000***		0.000***	0.000***
Other than single		0.609***	1.013***		-0.296***	-0.310***
Distance to the nearest health facility		-0.019***	-0.030***		-0.048***	-0.047***
Catholic		-0.132***	-0.032		-0.043	-0.054
Control	No	Yes	Yes	No	Yes	Yes
District FE	No	No	Yes	No	No	Yes
Year FE	No	No	Yes	No	No	Yes
Pseudo R-squared	0.103	0.208	0.351	0.002	0.113	0.115
No. of observations	68 298	68 279	68 279	24 840	24 833	24 833

Note: \*\*\*  $p < .01$ , \*\* $p < .05$ , \*  $p < .1$  This table presents the results of logistic regression of testing and HIV status on distance to nearest HIV prevention program. Columns (1) and (4) are a simple correlation between screening behavior and the primary outcomes. Columns (2) and (3) include control variables. Columns (3) and (6) add time-fixed effects. All estimates include controls for age, gender, marital status, wealth, rural/urban, religion, and distance to the nearest health center. Each column includes district fixed effects. All estimates are weighted using DHS sampling weights. The standard errors in parentheses are clustered at the survey cluster.

Table A1.7: Heterogeneity analysis - Intensity of exposure (HIV testing)

	Testing behavior		
	(1) Number of programs	(2) HIV programs	(3) Exposition before first intercourse
Exposed x Number of programs	0.008		
To be exposed x Number of programs	0.001***		
Exposed	-0.013		
To be exposed	0.011		
Exposed to any HIV program		0.010	
To be exposed to any HIV program		0.013*	
Exposed before sexual relationship			-0.072**
To be exposed			-0.020
Difference in differences	0.006	-0.003	-0.052**
F-test: active-inactive=0	2.391	0.140	4.365
p-value, F-test	0.12	0.71	0.04
Mean dep. var	0.543	0.543	0.556
R-squared	0.449	0.449	0.490
No. of observations	92 310	92 310	20 161

Note: \*\*\*  $p < .01$ , \*\* $p < .05$ , \*  $p < .1$  The table shows the results of the heterogeneous analysis according to the degree of exposure intensity for HIV testing. Three categories of exposure intensity are distinguished: the number of programs (column 1); whether or not exposed before the first sex (column 2); and exposure to any HIV program beyond prevention programs (column 3). All estimates include controls for age, gender, marital status, wealth, rural/urban and distance to the nearest health center. They include year and district fixed effects. All estimates are weighted using DHS sampling weights. The standard errors in parentheses are clustered at the survey cluster. The "Difference-in-Differences" indicates the difference between "Exposed" and "To be Exposed". The F-test and the p-value of the F-test are presented in the bottom section.

Table A1.8: Heterogeneity analysis - Intensity of exposure (HIV status)

	HIV status		
	(1) Number of programs	(2) HIV programs	(3) Exposition before first intercourse
Exposed x Number of programs	0.006		
To be exposed x Number of programs	0.001		
Exposed	-0.022		
To be exposed	0.009		
Exposed to any HIV program		0.002	
To be exposed to any HIV program		0.024	
Exposed before sexual relationship			-0.008
To be exposed			0.017
Difference in differences	0.005	-0.022	-0.025
F-test: active-inactive=0	1.650	2.743	1.757
p-value, F-test	0.20	0.10	0.19
Mean dep. var	0.102	0.102	0.120
R-squared	0.095	0.095	0.089
No. of observations	33 167	33 167	20 961

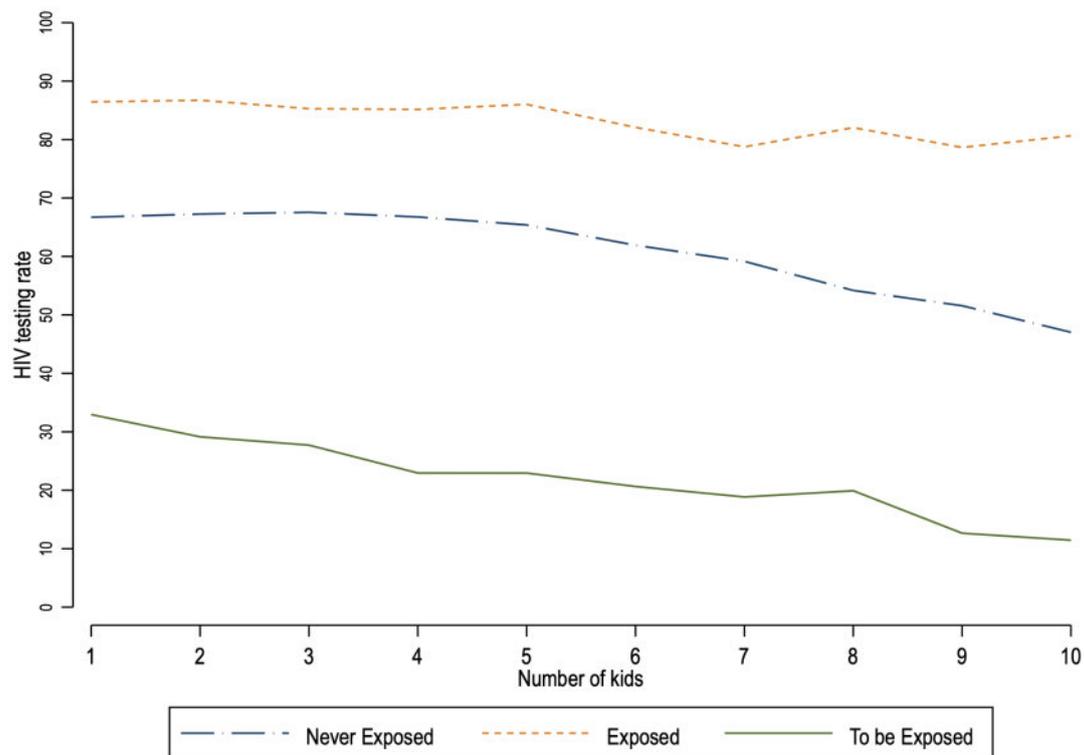
Note: \*\*\* p < .01, \*\*p < .05, \* p < .1 The table shows the results of the heterogeneous analysis according to the degree of exposure intensity for HIV status. Three categories of exposure intensity are distinguished: the number of programs (column 1); whether or not exposed before the first sex (column 2); and exposure to any HIV program beyond prevention programs (column 3). All estimates include controls for age, gender, marital status, wealth, rural/urban and distance to the nearest health center. They include year and district fixed effects. All estimates are weighted using DHS sampling weights. The standard errors in parentheses are clustered at the survey cluster. The "Difference-in-Differences" indicates the difference between "Exposed" and "To be Exposed". The F-test and the p-value of the F-test are presented in the bottom section.

Table A1.9: Heterogeneity analysis - Gender

	Testing behavior		HIV status	
	(1) Full sample	(2) Restricted sample	(3) Full sample	(4) Restricted sample
Exposed	0.020**	0.031	0.003	-0.017
To be exposed	0.006	0.018	0.017	0.049
Gender	-0.063***	0.040***	-0.023***	-0.042***
Exposed x Gender (Male)	-0.065***	-0.047*	-0.014	0.023
To be exposed x Gender (Male)	0.104***	-0.016	-0.014	-0.051
Difference in differences	-0.170	-0.031	0.000	0.074
F-test: active-inactive=0	81.967	1.280	0.000	3.302
p-value, F-test	0.00	0.26	1.00	0.07
Mean dep. var	0.543	0.403	0.627	0.482
R-squared	0.450	0.268	0.095	0.077
No. of observations	92310	18662	33167	9336

Note: The table presents the results of the heterogeneous analysis by gender. \*\*\* p < .01, \*\*p < .05, \* p < .1 This estimation includes interaction term between the treatment and the gender to assess heterogeneous effect by gender. It controls for age, marital status, wealth, rural/urban, and distance to the nearest health center. It includes year and district fixed effects and is weighted using DHS sampling weights. Columns (1) and (3) include all respondents. Columns (2) and (4) are restricted to men and women who ever had sexual intercourse and excluded women who were pregnant at least once to control for the free testing policy for mothers. The standard errors in parentheses are clustered at the survey cluster. The "Difference-in-Differences" indicates the difference between "Exposed" and "To be Exposed". The F-test and the p-value of the F-test are presented in the bottom section.

Figure A1.5: Robustness - Parallel trend



Note: This figure represents HIV testing rate among three groups: *Never Exposed*, *Exposed* and *To be Exposed*. The sample is restricted to women who are eligible to mandatory and free HIV screening during their pregnancy, since 2003. The outcome is plotted against the group of number of births given.

Table A1.10: Robustness - Entropy balancing

Variables	Treatment mean	Control mean (unweighted)	Standardized difference (before)	Control mean (weighted)	Standardized difference (after)
Gender of respondent	0.23	0.22	0.023	0.23	0.000
Respondent's current age	28.8	28.1	0.070	28.8	0.000
Education in single years	6.33	5.31	0.260	6.33	0.000
Rural	0.66	0.84	-0.377	0.66	0.000
Distance to the first health facility	3.65	3.86	-0.073	3.65	0.000
Wealth index	52997	7515	0.320	52960	0.000
Total births	2.77	2.92	-0.058	2.77	0.000
Religion (being catholic)	0.19	0.21	-0.052	0.19	0.000

Note: The table shows the result of matching treatment and comparison groups' observations on their propensity scores. The entropy balancing strategy builds a new weighting, adjusting inequalities in representation with respect to the first and second moments of the covariate distributions. The table displays the standardized differences between the two groups before and after applying the entropy balancing weighting.

Table A1.11: Robustness - Date of the last test

	Testing behavior		HIV status	
	Got tested (1)	(2)	Blood test result (DHS) (3)	(4)
Exposed (precision 1)	0.114***	0.028**	-0.018	-0.017
To be exposed (precision 1)	-0.338***	0.039**	0.020	0.008
Control	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Difference in differences	0.453***	-0.011	-0.037**	-0.024
F-test: active-inactive=0	1663.750	0.507	4.668	1.387
p-value, F-test	0.000	0.477	0.031	0.239
Mean dep. var	0.538	0.538	0.093	0.093
R-squared	0.16	0.45	0.10	0.10
No. of observations	70 182	70 182	25 875	25 875

Note: \*\*\* p <.01, \*\*p <.05, \* p <.1 This table presents the impact of exposure to HIV prevention program on screening (columns 1 and 2) and HIV status (columns 3 and 4). Contrary to the model presented in equation 1.1, the sample is restricted to people *Exposed* and *ToBeExposed* within a year before and after the survey. Additionally, people are said *Exposed* if they live in a 5/10km buffer around a program implemented before their last test (and not the interview date). People living in a 5/10km buffer of a program starting after their testing date (or interview date by default) are in the group *ToBeExposed*. People living further than a 5/10km buffer around the HIV prevention program are in the control group. The last date is estimated based on the date of the interview and the respondent's answer to: "When was your last test: a year ago? between 12 and 24 months? more than two years ago?". I take the previous year's date for those who answered "a year ago". I take the date 18 months ago for those who answered "between 12 and 24 months". I take the date two years ago for those who answered "more than 2 years ago". All estimates include controls for age, gender, marital status, wealth, rural/urban, religion, and distance to the nearest health center. They include year and district fixed effects. All estimates are weighted using DHS sampling weights. The standard errors in parentheses are clustered at the level of the survey's clusters. The main outcome is in the bottom part of the table, named "Difference-in-Differences." It indicates the difference between the coefficients "Exposed" and "To be Exposed." The F-test and the p-value of the F-test are presented in the bottom section.

Table A1.12: Robustness - Distance to HIV prevention program

	Testing behavior														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	11km	12km	13km	14km	15km	16km	17km	18km	19km	20km	21km	22km	23km	24km	25km
Exposed	-0.003	0.000	0.004	0.000	0.007	0.006	0.009	0.010	0.011	0.008	0.007	0.006	0.006	0.008	0.008
To be exposed	0.029***	0.026***	0.025***	0.020**	0.025***	0.023***	0.024***	0.023***	0.023***	0.018**	0.012*	0.012*	0.011	0.014*	0.012*
Difference in differences	-0.032***	-0.026***	-0.021***	-0.020***	-0.018***	-0.016**	-0.014**	-0.014**	-0.012*	-0.009	-0.005	-0.006	-0.005	-0.006	-0.004
F-test: active/inactive=0	14.474	10.157	7.064	6.665	6.232	5.303	4.375	4.148	3.330	2.129	0.702	1.084	0.698	1.062	0.465
p-value, F-test	0.00	0.00	0.01	0.01	0.01	0.02	0.04	0.04	0.07	0.14	0.40	0.30	0.40	0.30	0.50
Mean dep. var	0.544	0.544	0.544	0.544	0.544	0.544	0.544	0.544	0.544	0.544	0.544	0.544	0.544	0.544	0.544
R-squared	0.360	0.360	0.360	0.360	0.360	0.360	0.360	0.360	0.360	0.360	0.360	0.360	0.360	0.360	0.360
No. of observations	93,048	93,048	93,048	93,048	93,048	93,048	93,048	93,048	93,048	93,048	93,048	93,048	93,048	93,048	93,048

Note: The table replicates the main double-difference regression by expanding the distance bandwidth by 1km up to and including 19km. The results are robust up to and including 19km. \*\*\* p < .01, \*\* p < .05, \* p < .1 All estimates include controls for age, gender, marital status, wealth, rural/urban, religion and distance to the nearest health center. They include year and district fixed effects. All estimates are weighted using DHS sampling weights. The standard errors in parentheses are clustered at the survey cluster. The "Difference-in-Differences" indicates the difference between "Exposed" and "To be Exposed". The F-test and the p-value of the F-test are presented in the bottom section.

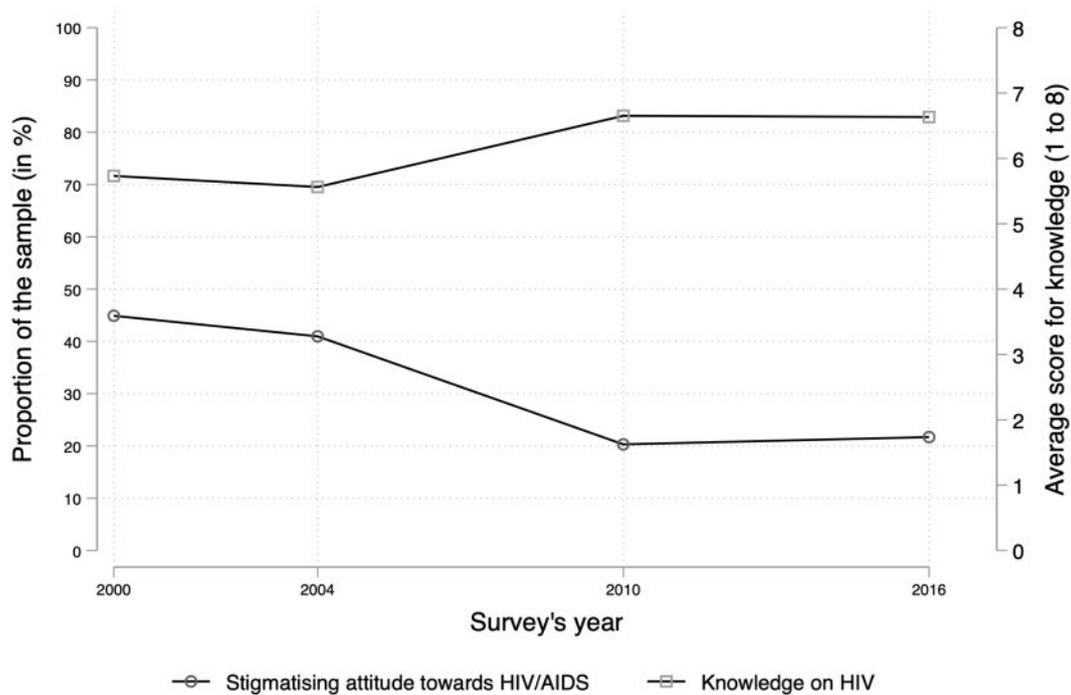
Table A1.13: Robustness - Survey wave, Sample weighting and completion date

	Testing behavior			HIV status		
	(1) Survey 2000	(2) Sampling weight	(3) Completion date	(4) Survey 2000	(5) Sampling weight	(6) Completion date
Exposed	0.006	0.013*		-0.004	0.004	
To be exposed	0.034**	0.026***		0.013	0.017	
Exposed (completion date)			-0.007			-0.010
To be exposed (completion date)			0.027***			0.017
Difference in differences	-0.028	-0.013	-0.034	-0.017	-0.013	-0.027
F-test: active-inactive=0	4.732	3.060	9.820	1.825	1.450	3.360
p-value, F-test	0.03	0.08	0.00	0.18	0.23	0.07
Mean dep. var	0.637	0.543	0.543	0.627	0.627	0.627
R-squared	0.379	0.452	0.449	0.095	0.093	0.095
No. of observations	76 160	92 310	92 310	33 167	33 167	33 167

Note: \*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .1$ . This table presents the impact of exposure to HIV prevention program on screening. All estimates include controls for age, gender, marital status, wealth, rural/urban, religion, and distance to the nearest health center. They include year and district fixed effects. All estimates are weighted using DHS sampling weights. The standard errors in parentheses are clustered at the level of the survey's clusters. The main outcome is in the bottom part of the table, named "Difference-in-Differences." It indicates the difference between the coefficients "Exposed" and "To be Exposed." The F-test and the p-value of the F-test are presented in the bottom section.

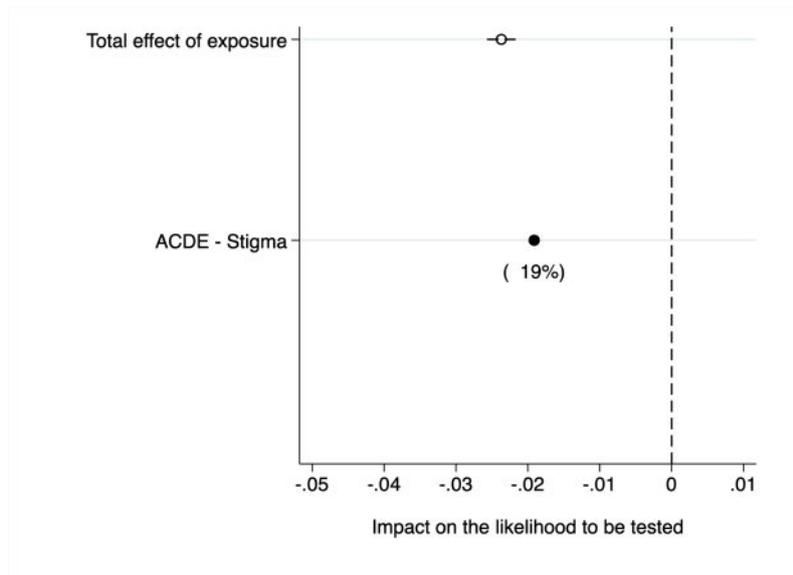
Columns (1) and (4) exclude the 2000 survey wave from the sample. Columns (2) and (5) do not use the sampling weight. Columns (3) and (6) include the end of the program in the regression. In other words, it is possible for an individual whose region was *Exposed* to be *To be Exposed* if the program ended before he or she was surveyed.

Figure A1.6: Knowledge level and stigmatizing attitude from 2000 to 2016



Note: The graph represents the trend of the knowledge level and stigmatizing attitudes over the years from 2000 to 2016 (DHS surveys). The stigmatizing attitude is a dummy taking the value 0 for those not declaring any stigmatizing attitude and 1 for those declaring at least one attitude stigmatizing seropositive people. See further information on table A1.15. The HIV knowledge score is rated from 0 to 8 based on the answer given to a list of questions on HIV.

Figure A1.7: Mediation analysis for stigma



Note: The graph presents the coefficient estimates at 90% confidence intervals of the impact of exposure to HIV prevention programs on the likelihood of getting tested. The total effect without mediation is reported in the coefficient “Total effect of exposure”. The “ACDE - Stigma” coefficient says the Average Controlled Direct Effect (ACDE). I consider only one mediator here: stigma.

Table A1.14: Questions in DHS surveys - Knowledge on HIV

	Survey's year			
	2000	2004	2010	2016
Can people get the AIDS virus from mosquito bites?	x	x	x	x
Can people get the AIDS virus by sharing food with a person who has AIDS?	x	x	x	x
Is it possible for a healthy-looking person to have the AIDS virus?	x	x	x	x
Can the virus that causes AIDS be transmitted from a mother to her baby: During pregnancy?	x	x	x	x
Can the virus that causes AIDS be transmitted from a mother to her baby: During delivery?	x	x	x	x
Can the virus that causes AIDS be transmitted from a mother to her baby: By breastfeeding?	x	x	x	x
Can people get the AIDS virus because of witchcraft or other supernatural means?		x	x	x
Are there any special medications that a doctor or a nurse can give to a woman infected with the AIDS virus to reduce the risk of transmission to the baby?		x	x	x

Note: This table lists questions on HIV raised in DHS from 2000 to 2016. I keep questions raised at least in 3 different surveys to build an index equal to 8 when the respondent gets all answers and 0 when the respondent answers incorrectly to all of them.

Table A1.15: Questions in DHS surveys - Attitude towards HIV

Year of survey	Questions
2016	Would you buy fresh vegetables from a shopkeeper or vendor if you knew that this person had HIV? Do you think children living with HIV should be allowed to attend school with children who do not have HIV? Do you fear that you could get HIV if you come into contact with the saliva of a person living with HIV?
2010	Would you buy fresh vegetables from a shopkeeper or vendor if you knew that this person had the AIDS virus? In your opinion, if a female teacher has the AIDS virus but is not sick, should she be allowed to continue teaching in the school ?
2004	Would you buy fresh vegetables from a shopkeeper or vendor if you knew that this person had the AIDS virus? In your opinion, if a female teacher has the AIDS virus but is not sick, should she be allowed to continue teaching in the school ? Should persons with the AIDS virus who work with other persons such as in a shop, office, or farm be allowed to continue their work or not?
2000	Should persons with the AIDS virus who work with other persons such as in a shop, office, or farm be allowed to continue their work or not?

Note: This table presents the questions about the attitude towards HIV in the successive DHS surveys. The variable is a dummy equal to 0 (no answer denoting negative attitude towards HIV) or 1 (at least one answer denoting negative attitude toward HIV). Those questions are part of the DHS section entitled "HIV and other sexually transmitted infections." The latter includes other questions relative to feelings towards stigma that I exclude to build the variable on stigma. Stigma is a three-dimensional social and individual reality, but I only include those leading to enacted stigma. The enacted stigma "results when clandestine hostility and/or overt acts of discrimination are directed towards persons specifically because they possess the stigmatized attribute" (Tsai et al. 2013), Allport et al. (1954)). The internalized stigma "results when stigmatized persons come to accept these inhospitable attitudes as valid, thereby developing self-defacing beliefs and perceptions about themselves" (Tsai et al. 2013). The anticipation of stigma names people's expectations of their community's attitude against HIV-positive or assumed HIV-positive individuals. Thus, I select questions on enacted stigma because it is expected that they will be the ones that most closely reflect the translation of the feeling of stigma into real action and because they were repeated in all four waves of the survey. The questions related to the anticipation of stigma are not used since they were only asked in 2016.

Table A1.16: Description Foreign aid-funded HIV prevention programs in Malawi (1997-2017)

Name of the project	Donor	Locations (district)
Behaviours adopted that reduce fertility and risk of HIV/AIDS	USAID	Blantyre, Lilongwe, Mzimba, Zomba
Community based family planning (FP) and HIV/Aids services	USAID	Balaka, Chikwawa, Karonga, Kasungu, Mangochi, Nkhotakota, Phalombe, Salima
District-level implementation of the Malawi HoH PMTCT Programme	Norwegian Agency for Development Cooperation	Machinga, Mangochi
Extending Quality Improvement for HIV/AIDS in Malawi (EQUIP)	USAID	Lilongwe
HIV Prevention Communication	Canadian International Development Agency	Chikwawa, Kasungu, Mzimba
HIV Prevention for out of sch Adol & Yth	Federal Republic of Germany & Global Fund	Blantyre, Chikwawa, Dedza, Lilongwe, Mzimba
HIV Prevention in Sch Adolescents & Youth	United Nations Children's Fund	Balaka, Dedza, Lilongwe, Mzimba, Nsanje
JHU-BRIDGE	USAID	Blantyre, Chikwawa, Chiradzulu, Machinga, Mulanje, Mwanza, Neno, Nsanje, Phalombe, Thyolo, Zomba
Norwegian Church Aid-health training	Norwegian Agency for Development Cooperation	Blantyre, Chiradzulu, Kasungu, Lilongwe, Mulanje, Mzimba, Nsanje, Thyolo, Zomba
PMTCT and Paediatric AIDS	Canada	Balaka, Chikwawa, Chitipa, Dedza, Ksungu, Lilongwe, Mzimba, Nsanje, Ntcheu, Thyolo
Project Hope Malawi	USAID	Mulanje, Phalombe
Promote Normative Change	USAID	Balaka, Blantyre, Chikwawa, Chiradzulu, Kasungu, Machinga, Mangochi, Mulanje, Mwanza, Mzimba, Neno, Nsanje, Ntcheu, Phalombe, Salima, Thyolo, Zomba
Safeguarding Young People Programme - New	The European Union & Swiss Development Cooperation	Blantyre, Dowa
Safe Motherhood Project (TC)	UK Department for International Development	Chikwawa, Dedza, Mangochi, Nkhata Bay
Strengthening the Delivery, Coordination, and Monitoring of HIV Services in Malawi through Faith-Based Institutions	Centers for Disease Control & Prevention	Blantyre, Dowa, Kasungu, Mzimba
Strengthening expanded HIV/AIDS Counseling & Testing services in Malawi	Centers for Disease Control & Prevention	Blantyre, Kasungu, Mzimba
Strengthening expanded HIV/AIDS Counseling & Testing services in Malawi (MACRO)	Centers for Disease Control & Prevention	Blantyre, Lilongwe, Mangochi, Rumphu

Note: This table presents the name, the donor and the location of HIV prevention programs listed in the databases of [Peratsakis et al. \(2012\)](#) and the Ministry of Finance.

## Chapter 2

# Adopting PrEP preventive treatment in the sex market in Côte d'Ivoire

### Abstract

Since 2015, the WHO has been advocating for the dissemination of Pre-exposure Prophylaxis (PrEP) among Female Sex Workers (FSWs). Yet studies find low adherence among FSWs. This paper tests the hypothesis that adherence to treatment depends on the heterogeneity on the cost-benefit between preventive health and risky sexual behavior. It defines a theoretical framework for preventive treatment adherence. The theory is empirically tested with a simultaneous equations model. It uses a new database collected from November 2019 to April 2021 in San Pedro (Côte d'Ivoire), as part of the project PRINCESSE ANRS 12381. The attrition to the project captures non-adherence to PrEP. Estimates show that treatment adherence varies with the number of sexual intercourse. Having fewer clients significantly increases the likelihood of dropping treatment. These results are consistent with theoretical predictions. The effect is stronger for those who do not believe in the treatment efficiency. This paper complements previous studies on PrEP impact on risk compensating behavior among FSWs.

**Keywords:** treatment adherence, attrition, female sex workers, PrEP, simultaneous equations model.

**JEL Codes:** I12, I15, J24, O15, D91.

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## 1 Introduction

Research on antiretroviral therapy took a big leap forward in 2012 when the United States Food and Drug Administration approved Pre-exposure prophylaxis (PrEP) for HIV prevention.<sup>1</sup> PrEP is an antiretroviral drug taken daily by seronegative people to reduce by up to 99% the likelihood of contracting HIV (Cohen et al. 2011, van der Straten et al. 2012, Grant et al. 2010). In 2015, the World Health Organization (WHO) urged governments to provide the treatment for “all population groups at substantial risk of HIV infection”, among which Female Sex Workers (FSWs) (WHO 2015, Bharat Bhushan Rewari et al. 2017). FSWs require “enhanced HIV testing, treatment, and prevention programs” (Bekker et al. 2018) since they are “around 11 times more likely to be HIV infected than women in the general population (Baral et al. 2012)”. PrEP is of interest for the health of FSWs and the regulation of the epidemic (Irungu and Baeten 2020) for countries where FSWs and their clients are the main vectors for HIV spread, such as Côte d'Ivoire (Maheu-Giroux et al. 2017). However, studies (Mboup et al. 2021, Eakle et al. 2017, 2018) show a low adherence. Retention rate to treatment in Benin and South Africa were at 47% and 22% respectively after 12 months.<sup>2</sup> On the other side, the risk compensation theory questions the efficiency of PrEP (Cassell et al. 2006, Quaife et al. 2018). Treatment recipients would increase condomless sex supply to get a price premium (Rao et al. 2003, Gertler et al. 2005, Arunachalam and Shah 2013), which would reduce the positive effect of PrEP on HIV infections (Quaife et al. 2021) and could increase sexually transmitted diseases (Wilson et al. 2014).

The WHO broadly defines adherence as “the extent to which the persons’ behavior (including medication-taking) corresponds with agreed recommendations from a healthcare provider” (Sabaté and Sabaté 2003). It is needed to distinguish primary from secondary non-adherence.<sup>3</sup> The former is defined as “the frequency

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<sup>1</sup>US Food and Drug Administration. The FDA approved the first drug to reduce the risk of sexually acquired HIV infection in 2012. <http://www.fda.gov/NewsEvents/Newsroom/PressAnnouncements/ucm312210.htm>

<sup>2</sup>Another study by Reza-Paul et al. (2020) has a retention rate of 97% after 16 months, which might be correlated with the enrolment condition of not moving from the operational site during the project.

<sup>3</sup>The expressions of adherence and non-adherence are transposable as long as the economic interpretation is in line. The theoretical part will use the expression “adherence” and the empirical

with which patients fail to fill prescriptions when new medications are started so it is related to refilling and initiation of the medication therapy” (Lam and Fresco 2015). It includes retention and adherence to treatment follow-up, referred to as treatment non-adherence hereafter<sup>4</sup>. Whereas secondary non-adherence refers to retention to treatment and is defined as “the medication being [...] taken as prescribed when prescriptions are filled.” (Lam and Fresco 2015). Secondary non-adherence is referred to as treatment compliance hereafter.

This paper presents new evidence on the mechanisms of non-adherence to PrEP treatment. Results show that non-adherence is due to heterogeneity in the cost-benefit analysis for adherence. Specifically, having more sexual intercourse in the work place<sup>5</sup> decreases the probability of dropping the treatment. The number of occupational sexual intercourse captures FSWs’ sexual risks of contracting HIV.

The study uses Lamiraud and Geoffard (2007) ’s model of patient’s adherence behavior. (Non-) Adherence to treatment results from an individual’s cost-benefit analysis based on observable and unobservable covariates. Their model shows that the patient’s choice of adherence reveals their welfare, determined by their health and treatment secondary effects. In this paper, the theoretical model is adapted to preventive treatment for FSWs. It includes a new parameter in Lamiraud and Geoffard (2007)’s model in the number of occupational sexual intercourse that estimates HIV risks. It relies on the hypothesis that the only observable for FSWs to estimate HIV infection is the number of sexual intercourse. Indeed, FSWs cannot observe the benefit of an HIV preventive treatment on health except if it fails, meaning the person is infected. Consequently, they decide to adopt treatment based on their occupational sexual activities.

In contrast to Lamiraud and Geoffard (2007), this study does not rely on a randomized control trial (RCT) to test this assumption but uses a quasi-experiment.

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part the notion of “non-adherence”.

<sup>4</sup>Sometimes it will be referred to treatment adherence rather than treatment non-adherence. Treatment adherence is then defined as ‘the frequency with which patients [attends medical appointment] to fill prescriptions when new medications are started so it is related to refilling and initiation of the medication therapy”.

<sup>5</sup>Referred hereafter as professional or occupational sexual intercourse.

The empirical strategy uses a simultaneous equations model to tackle the reverse causality between adherence and the number of occupational sexual intercourse. It includes one equation for non-adherence and another for the number of occupational sexual intercourse. Quasi-experimentation with a longitudinal database gives three advantages over a RCT to study the preventive health behavior of FSWs. First, longitudinal data collected is used for descriptive and exploratory analyses for all determinants of adherence, and not only specific ones. The second pitfall is that the simple set of a RCT intervention would have an incentive effect on adherence, like keeping a sex diary may improve productivity and the sex supply. Finally, the quasi-experiment follows ethical rules that provide access to treatment to all members of an at-risk population and at the same time.

The database is a novel longitudinal survey conducted in San Pedro, Côte d'Ivoire between November 2019 and April 2021 by the project PRINCESSE ANRS 12381 (Becquet et al. 2021). FSWs were offered free sexual and reproductive health care, including PrEP treatment for HIV-negative FSWs. The empirical analysis takes advantage of the panel database to measure treatment non-adherence with FSWs attrition to the project. As a non-random event, like it is in this case, attrition is often correlated to individual characteristics (Alderman et al. 2001) and could be used to reveal patients (Lamiraud and Geoffard 2007, Cheng and Trivedi 2015) or students welfare (Stock et al. 2006). In this paper, attrition reveals FSWs the outcome of a cost benefit analysis of adherence to treatment.

This paper relates to three strands of literature. First, it contributes to understanding treatment adherence, notably preventive treatment adherence. According to Bouckaert and Schokkaert (2016), the adoption of preventive treatment depends on the type of disease. Lamiraud and Geoffard (2007) and Chan and Hamilton (2006) focus on curative treatment and highlight that non-adherence to treatment should be considered as a rational decision reflecting patient well-being under treatment. Ghayda et al. (2020) review possible determinants of discontinuation in HIV prevention medication such as stigma, lack of education, the economic burden of the treatment, and the daily posology of the treatment. To our knowledge, this study proposes the first stylized theoretical framework adapted to FSWs' treatment

adherence that considers sexual intercourse as a health parameter. The empirical strategy does not include risk perception because of data availability, although it may impact treatment adherence. For instance, [Etner and Jeleva \(2013\)](#) use a model of recursive rank-dependent utility and find that pessimistic and fatalistic individuals adopt primary preventive treatment.

Second, this research is at the intersection of the literature on risky sex supply and risk premium. [Rao et al. \(2003\)](#) revealed the premium on the provision of unprotected sex increases the income of sex workers. According to [Gertler et al. \(2005\)](#), the mere benefit of this premium justifies sex workers balancing the risk of infection against the income benefit of unprotected sex. [Arunachalam and Shah \(2013\)](#) highlight that the premium is also a compensation for the risk of contracting a sexual transmitting infection since it would decrease the supply of sex and thus the income from sex work ([Robinson and Yeh 2011](#)). Women are all the more at risk that negative income shocks increase the marginal supply of sex and the marginal supply of unprotected sex, as shown by [Robinson and Yeh \(2011\)](#), [Jones and Gong \(2021\)](#), and [Gong et al. \(2019\)](#). According to [Quaife et al. \(2018\)](#), the introduction of PrEP would increase condomless sex supply and decrease the price premium for condomless sex. If PrEP were to change sexual supply behavior, the treatment's positive effect on reducing the spread of HIV would be smaller ([Quaife et al. 2021](#)). Although robust, [Quaife et al. \(2018\)](#) study is based on a discrete choice experiment that cannot assess the dropping treatment adherence over time ([Mboup et al. 2021](#), [Eakle et al. 2017, 2018](#)) and cannot explore its mechanisms. This paper further contributes to findings on the impact of PrEP on sex supply, but it reveals the importance of occupational sexual activity on PrEP non-adherence.

Eventually, the empirical analysis is in line with studies highlighting the importance of observed and unobserved heterogeneity in technology adoption in health, education, or agriculture ([Suri 2011](#)). Research in technology adoption usually relies on a correlated random effect model to tackle the structural endogeneity between the choice of technology adoption and its return. The structural form of treatment adherence would show a correlation between adherence and return to adherence. This correlation is the core hypothesis in the study of [Quaife et al. \(2018\)](#) on the risk

premium attitude. This paper cannot rely on the correlated random effect model (Wooldridge 2019) due to data scarcity (the number of clients per hour). However it shows that the impact of heterogeneity on cost-benefit analysis for treatment adherence<sup>6</sup> can be revealed with the simultaneous equations model using the Mundlak procedure in the non-linear regression for treatment non-adherence (Wooldridge 2010, 2015).

The paper proceeds as follows. The theoretical model of treatment adherence is introduced in section 3. Section 3 presents the context of the program and summary statistics of the sample. Then, section 5 gives descriptive evidence on PrEP adherence and details the econometric framework. Results are reported and discussed in section 6.

## 2 Stylized theoretical framework

Lamiraud and Geoffard (2007) model treatment adherence to HIV antiretroviral as a function of health and well-being. Treatment adherence depends on “perceived costs” and “observed” benefits. They find that treatment drop-out at  $t$  increases because of treatment’s negative side effects at  $t - 1$  (measuring well-being), even if the treatment effectively impacted health (CD4 cell counts).

Consider Lamiraud and Geoffard (2007) model of treatment adherence in which a utility function represents one individual’s preferences before treatment  $u(h, q)$ ; where  $h$  is the patient’s health status and  $q$  is her level of well-being. Once the treatment is introduced, the decision to adhere to treatment results from a trade-off between the benefits of the treatment on one’s health status,  $k$ , and the negative side effects on well-being,  $c$ . The utility function after treatment was therefore  $u(h + k, q - c)$ .

The main assumptions of the utility function are:  $u_h > 0$ ,  $u_q > 0$ ,  $u_{hh} < 0$ ,  $u_{qq} < 0$  and  $u_{hq} = u_{qh} \geq 0$ . A patient is totally adherent if  $\theta = 1$  and is not adherent at all if  $\theta = 0$ . If a patient adheres, Lamiraud and Geoffard (2007) note that the well-being is  $q' = q - c\theta$  and the health status is  $h' = h + k\theta$ , where  $c$  is the cost associated with the treatment and  $k$  is the treatment benefit on health.

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<sup>6</sup>The cost-benefit analysis includes the risk to contract HIV that is captured by the number of occupational sexual intercourse.

The model presented hereafter adapts the adherence model from [Lamiraud and Geoffard \(2007\)](#) to preventive treatment for HIV for FSWs. FSWs are initially HIV-negative and at risk of contracting the disease. An effective PrEP treatment is measured by the absence of variation in health state since HIV is a non-reversible infection. Thus, a FSW under PrEP cannot objectively observe treatment efficiency except when it fails, i.e., in the case of HIV infection. However, they can predict their probability of contracting HIV by relying on their sexual behavior, assuming they are rational. The model includes a new parameter at  $t - 1$ , which is the number of occupational sexual intercourse (number of clients)  $s$  and acts as a proxy for the risk of contracting HIV. As occupational sexual interactions happen with multiple individuals, it is associated with the risk of contracting HIV. The parameter  $s$  excludes private sexual intercourse because it usually happens with one partner<sup>7</sup>.

The treatment  $k$  will impact the health status if and only if  $s$  is non-zero or strictly positive and will depend on its efficiency. For a preventive treatment such as PrEP, treatment efficiency depends highly on compliance with the prescription. As presented below, the study does not monitor compliance with daily dosage<sup>8</sup>. Thus, the study cannot estimate the objective treatment efficiency and the assumption of the empirical analysis is a time-constant compliance (see section 5). This limit is discussed in section 6 that presents an heterogeneity analysis with FSWs' perception of treatment efficiency.

As a consequence, the health status is  $h' = h - \frac{s}{1+k\theta}$ . The *new* utility function before the preventive treatment is  $u(h - s, q)$  and the *new* utility function after treatment is  $u(h - \frac{s}{1+k}, q - c)$ .

The impact of the number of sexual interactions  $s$  on well-being is uncertain as they could be positively correlated if the income is negatively correlated with

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<sup>7</sup>This assumption simplifies the risk of contracting HIV, which is more complex and rather incorporates the number of sexual interactions, the type of sexual interaction and timing of the sexual interaction. It considers too that the treatment reduces 100% of the risk of contracting HIV while in fact, there is a tiny 1% risk that the treatment may fail to protect. However, I would need a larger sample than the one I have to have the statistical power to test this hypothesis (which is not desirable).

<sup>8</sup>The model relies on the hypothesis that FSWs are compliant. Compliance means that FSWs take their drug according to the posology prescribed.

psychological well-being, as a spillover of occupational sexual activity. Thus, well-being is defined as in Lamiraud and Geoffard (2007). The treatment's physical and psychological side effects,  $c$ , may deteriorate FSW's well-being,  $q$ , such that:  $q' = q - c\theta$ . Thus, the utility level is given by:  $u(h - \frac{s}{1+k}, q - c)$  if  $\theta = 1$  and  $u(h - s, q)$  if  $\theta = 0$ .

*New threshold function*

The treatment adherence depends on a threshold level  $k(c; h, q, s)$  that increases or decreases with  $c$ ,  $h$ ,  $q$  and  $s$ .

The threshold  $k$  decreases with  $s$ . We show that the sign of the derivative  $k_s$  is negative. By definition, the threshold is the level where the utility after treatment is superior to the utility before treatment. The threshold is determined by the equation:

$$\Delta(k, c; h, q, s) = u(h - \frac{s}{1+k}, q - c) - u(h - s, q) = 0 \quad (2.1)$$

Like Lamiraud and Geoffard (2007), I use the implicit function theorem (IFT) that states, from equation 2.1:

$$k_s = \frac{-\Delta_k}{\Delta_s} \quad (2.2)$$

By direct derivation of  $\Delta$ , we can write:

$$\Delta_k = \frac{s}{1+k^2} u_h(h - \frac{s}{1+k}, q - c) \quad (2.3)$$

and

$$\Delta_s = \frac{-1}{1+k} u_h(h - \frac{s}{1+k}, q - c) + u_h(h - s, q) \quad (2.4)$$

and since  $k_s = \frac{-\Delta_k}{\Delta_s} \Rightarrow \frac{1}{k_s} = \frac{-\Delta_s}{\Delta_k}$  then

$$\frac{1}{k_s} = \frac{-\Delta_s}{\Delta_k} = \frac{1+k}{s} - \frac{1+k^2}{s} \frac{u_h(h - s, q)}{u_h(h - \frac{s}{1+k}, q - c)} \quad (2.5)$$

By assumption,  $u_{hq} \geq 0$  so  $\frac{u_h(h-s,q)}{u_h(h-\frac{s}{1+k},q-c)} > 1$

Therefore,

$$\frac{1}{k_s} \leq \frac{1+k}{s} - \frac{1+k^2}{s} < 0 \quad (2.6)$$

Eventually,

$$\frac{1}{k_s} < 0 \Rightarrow k_s < 0 \quad (2.7)$$

So  $k$  decreases with  $s$ . In other words, while the number of sexual intercourse increases, it lowers the threshold until the utility to adhere to the treatment is equal or superior to the utility without treatment. Then, the FSW adopts the treatment.

The threshold  $k$  increases with  $c$  and  $h$ , and decreases with  $q$ . The proof of Proposition 2 follows a similar logic as the proof of Proposition 2. See Appendix 6.

### 3 Context

This study uses a unique database collected among FSWs in San Pedro (Côte d'Ivoire) as part of the PRINCESSE project (see section 3.1). Summary statistics of this original sample are provided in section 3.2.

#### 3.1 Setting

FSWs in Côte d'Ivoire are at high risk of HIV infection. In 2014, HIV prevalence among FSWs was 4.8% in Côte d'Ivoire (UNAIDS 2020) and 11.4% in Abidjan (Bamba et al. 2014). HIV incidence was 3.2% in San Pedro in 2016-2017 (Nouaman et al. 2018). Sex work takes place in a legal vacuum. The law states the right of ownership and free use of one's body but it prohibits street sollicitation and the organisation of sex activities. As of 2019, Côte d'Ivoire has been working to implement the WHO recommendations for PrEP.

This research uses a unique database collected since November 2019 in the

project PRINCESSE ANRS 12381 (Becquet et al. 2021). The project aims to “develop, document, and analyze a community-based care package combining testing, combination prevention, including pre-exposure prophylaxis (PrEP), immediate HIV treatment, hepatitis B management, and sexual and reproductive health (SRH) in order to reduce HIV exposure among FSWs and their partners in Côte d’Ivoire”.<sup>9</sup> We collected a unique database to help understand FSWs’ preventive behavior and the benefits of public health policy. The setting presents econometric challenges since the project’s primary goal is different, also close to the research question raised in this study. The following sections will present the econometric analysis of stylized facts about FSWs’ adherence to preventive treatment.

FSWs of San Pedro and its suburbs (Côte d’Ivoire) are offered free sexual and reproductive health care within a mobile medical clinic run by Prosama<sup>10</sup>, a local non-governmental organization settled in an integrated health center. The mobile clinic navigates between ten identified sex work sites every two weeks<sup>11</sup> to provide free medical drugs and services<sup>12</sup> among which the PrEP treatment, for HIV-negative FSWs. Any woman aged 18 and older who identifies as a female sex worker and agrees to participate in the project would benefit from it with the right to leave it at any moment without notice.

On the enrolment day, the FSWs have a first medical appointment, during which the social worker conducts a socio-demographic survey. This survey is used as baseline data. The FSWs undergo medical and biological interviews, including testing for HIV, Hepatitis B, Hepatitis C, and STIs. They are introduced to PrEP to assess whether they are interested. Table A2.3 indicates that 77% of FSWs had a presentation about the drug during the first appointment. This variable has a correlation with the non-initiation of PrEP<sup>13</sup>. They are invited to return two weeks after this first appointment to receive their medical results. Two weeks later, the

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<sup>9</sup>See appendix 6 that details the project’s context and goals.

<sup>10</sup>The name was altered to protect the anonymity of the NGO and its beneficiaries.

<sup>11</sup>It was initially supposed to change location on a weekly basis, but the lack of medical equipment made it less frequent.

<sup>12</sup>Medical services are HIV screening, vaccination, and treatment for HIV, hepatitis B, and other sexually transmitted infections; medical assistance for HIV positive FSW; contraceptive pills, intra-uterine device, implants, and menstrual cups.

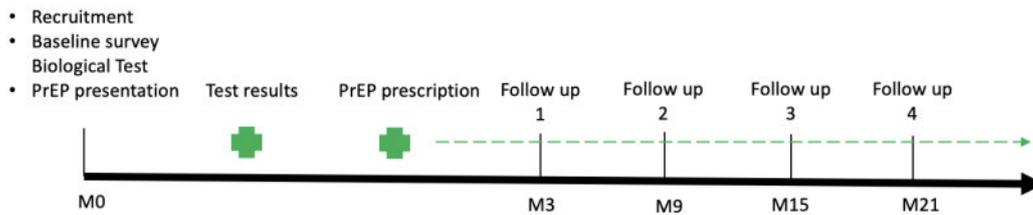
<sup>13</sup>The initiation refers to adopting the treatment for the first time.

doctors offer to prescribe PrEP to HB and HIV-negative FSWs. If the sex worker expressed an interest in PrEP at the first appointment, they can still change their minds at any moment and refuse to use it.

Returning to renew the PrEP prescription on time is the variable to measure the outcome of treatment adherence. Adherence is the action taken by the patient regarding their medication, like filling and refilling their prescription, the dosage recommendations, following the correct schedule, and fulfilling the period needed for effective treatment. It is different from compliance, which was not monitored. Indeed, monitoring their compliance could have induced confirmation bias behaviors. The prescription usually lasts for a month or two, and its renewal should be before its end. FSWs could only get their prescription in the medical truck or the physical center in San Pedro. However, some FSWs came back too late, from one to several weeks after the end of the prescription. If they return several weeks after missing their appointment to renew the prescription, they are introduced to PrEP again. Thus, some were introduced to PrEP several times (see figure [A2.3](#)). Some never came back after the first prescription. Non-adherence is measured with these inconsistencies in following PrEP treatment given as part of the PRINCESSE program.

In parallel to their appointment to renew their PrEP prescription, four follow-up surveys were scheduled after the baseline to collect bio-medical information and to complete a socio-demographic survey. The follow-up occurs when the FSW returns to renew her treatment at month 3 (M3), month 9 (M9), month 15 (M15), and month 21 (M21). FSWs could refuse to participate in these interviews, but 85% of the 200 HIV-negative participants accepted the follow-up survey.

Figure 2.1: A FSW's journey on Princesse project



Note: This scheme present the FSW's journey on the project. FSWs were continuously recruited and could join the project at any moment. At their recruitment, each FSW is going through a baseline interview carried out by the doctor and the social worker, and some medical and biological tests to establish STIs, HIV and HB status. The doctor also presented PrEP to assess whether the FSW is interested in the treatment. Following this first meeting, the FSW is invited to come back in order to discuss her HIV status. If she is negative and interested in it, the doctor prescribed the PrEP. The FSWs can visit the mobile to be prescribed the PrEP or anything else as they can join the project and refuse PrEP. They were interviewed first at the recruitment, then three months after and every six months after. They were not bounded to attend the interview and some missed it or postponed the date. In practice, most of the follow up surveys were not run on due date but it was considered on time within a two-month frame-time.

## 3.2 Summary statistics

Table 3.2 reports socio-demographic characteristics of the 330 enrolled FSWs. At baseline, most FSWs were Ivoirian, aged 31 on average, with 4 years of experience in sex work. Sex work accounts for a significant part of their professional income since 92% worked every day in the previous month, although less than half of the sample - 48% - declared that sex work is their main job. The low literacy level and the high HIV prevalence rates suggest a vulnerability of women to their professional activity and financial dependence on sex work. The HIV prevalence rate, presented in table A2.3, is almost three times higher than the national one; 18% of the sample have STD / STI symptoms, and 32% have had condomless sexual intercourse.

Table 2.1: Descriptive summary split by prescription groups

	All N=330	Not prescribed N=130	Prescribed N=200	2*p-value	2* N
Age	30.7 (7.88)	31.2 (9.08)	30.4 (6.99)	0.400	330
Nationality (Ivorian)	0.58 (0.49)	0.55 (0.50)	0.60 (0.49)	0.462	330
Level of education:				0.121	327
Never went to school	34.3%	32.0%	35.7%		
Coranic school	1.22%	3.12%	0.00%		
Primary school	33.3%	31.2%	34.7%		
Secondary school	26.0%	28.9%	24.1%		
Higher education	5.20%	4.69%	5.53%		
Sex work as main job	0.48 (0.50)	0.47 (0.50)	0.49 (0.50)	0.713	330
Work everyday last month	0.92 (0.27)	0.91 (0.28)	0.92 (0.26)	0.705	325
Years of experience	3.74 (4.29)	3.43 (3.84)	3.94 (4.55)	0.283	323
Works in a brothel:				0.154	330
No	49.1%	43.8%	52.5%		
Yes	50.9%	56.2%	47.5%		
Had condomless intercourse (baseline):				0.112	329
No	67.8%	72.3%	64.8%		
Yes	31.9%	26.9%	35.2%		
Don't answer	0.30%	0.77%	0.00%		
Number of clients (baseline)	4.59 (3.03)	4.39 (2.97)	4.71 (3.07)	0.384	287
Threshold price (baseline)	1625 (849)	1650 (949)	1609 (784)	0.698	298
Was introduced to PrEP	0.82 (0.38)	0.57 (0.50)	0.98 (0.12)	<0.001	330
Was interested in PrEP	0.82 (0.39)	0.55 (0.50)	0.98 (0.12)	<0.001	330
Was introduced to PrEP - 1st visit	0.77 (0.42)	0.57 (0.50)	0.90 (0.30)	<0.001	330

Note: The table presents summary statistics among FSWs who were recruited. The columns "All", "Not prescribed", "Prescribed" presents mean and standard deviations in brackets of three groups: the full sample, those who were prescribed PrEP and those who were not prescribed PrEP. The p-value is computed from the Pearson test when row-variable is normal and from the Spearman test when it is continuous non-normal. If the row-variable is categorical, the p-value for trend is computed from Mantel-Haenszel test of trend. The last column gives the total number of observations available for each variable.

FSWs were recruited from November 2019 to April 2021 on various sex work sites (see figure A2.1), such as brothels, hostels, or streets, with the help of peer educators and a snowball technique to obtain a representative sample of FSWs.<sup>14</sup> Their demographic characteristics are highly correlated (table A2.2). On the one hand, foreign FSWs working in brothels are more likely to consider sex work as their main job and thus to have worked every day in the previous month. They rent their room where they live and work. On the other hand, nationality and the place of work determine the sexual and health behaviors. Foreign FSWs living in brothels and working daily are less likely to have unprotected sex. Being an old Ivorian

<sup>14</sup>This study does not use data collected after April 2021 because FSWs were proposed in-kind compensation, milk, in addition to monetary compensation for transport costs. Milk is the answer to their request. It was better not to include data collected after since it could be an incentive to return, although preliminary results show no impact on FSWs' attendance or enrolment.

working in a brothel increases the likelihood of being HIV-positive while being a young Ivorian working in a brothel increases the likelihood of not using a condom in the last seven days.<sup>15</sup>

## 4 Empirical analysis

FSWs adhere to the treatment only if its benefits exceed its costs, both captured by health and well-being in the theoretical model (see section 3). The following section tests the hypothesis that the number of sexual intercourse is positively associated with an expected return on treatment. Sub-section 4.1 details how attrition to PRINCESSE program is used to measure adherence to PrEP. Sub-section 4.2 gives descriptive evidence on the determinants of adherence, specifically the number of clients and other confounding variables. Eventually, sub-section 4.3 presents the simultaneous equations model used to tackle the endogeneity bias between treatment adherence and the number of clients.

### 4.1 Measuring adherence with attrition

Attrition to the health program has been used to measure treatment adherence and overcome the social desirability bias common in declarative surveys. Chan and Hamilton (2006) and Lamiraud and Geoffard (2007) claimed that treatment non-adherence, captured by attrition, shall be interpreted as rational behavior, contrasting with previous literature for which attrition was irrational (Parsons 1951), a statistical bias (Scharfstein et al. 1999) or due to a cost problem (Cleemput et al. 2002, Hughes et al. 2001). Treatment drop-out resulted from a cost-benefit analysis comparing the treatment's direct impact on health and its spillovers on well-being. The latter increased the opportunity cost so high that people would rather drop it.

Attrition is used as a proxy of PrEP adherence since the FSWS were allowed to

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<sup>15</sup>One concern was the correlation between the work experience and the sexual behavior. The literature has underlined that incoming and inexperienced FSWS are more likely to engage in condomless sexual intercourse, which does not appear in table A2.2. FSWS less experienced (one year or less) have been increasingly visiting the clinic until May 2020, before it dropped and increased again. This trend parallels the number of clients declared during the follow-up surveys (red line of figure A2.4).

leave the project without notice. The assumption holds that if FSWs joined the program for nothing other than PrEP, they would lose by leaving the program. The medical truck offers free access to healthcare, which could be a reason for joining the program. However, FSWs had access to free healthcare in Prosama physical clinic for years before implementing the PRINCESSE program. A second reason for FSWs to join the program would be the privacy given by the mobile clinic. Although the mobile clinic was designed to remain discrete, it is possible that after several weeks, it would be recognized by neighbors and clients. Participants could refuse to come back. This possibility cannot be dismissed based on the available data. However, the PRINCESSE program has exclusivity to prescribe free PrEP in San Pedro and its suburbs. Table 3.2 shows a high rate of PrEP initiation, 90% of FSWs introduced to PrEP at their enrolment were prescribed the drug. By leaving the project temporarily or definitively, FSWs would knowingly lose access to PrEP.

Figure A2.2 shows that PrEP was presented to 271 FSWs, and 200 of them were effectively prescribed the drug.<sup>16</sup> FSWs who were not introduced to PrEP at their first visit were less likely to be prescribed PrEP. Forty-three percent of FSWs who were never prescribed PrEP but were introduced to it, did not return, maybe because they were neither interested in PrEP nor other healthcare. Only 28 participants who were never prescribed PrEP came back for a second visit<sup>17</sup>, which indicates they came back for other healthcare services provided in the mobile clinic. Nineteen participants were introduced to PrEP and were interested in it but never agreed to be prescribed PrEP<sup>18</sup>. The latter, representing 5% of the total sample, are not interested in PrEP but other medical services.

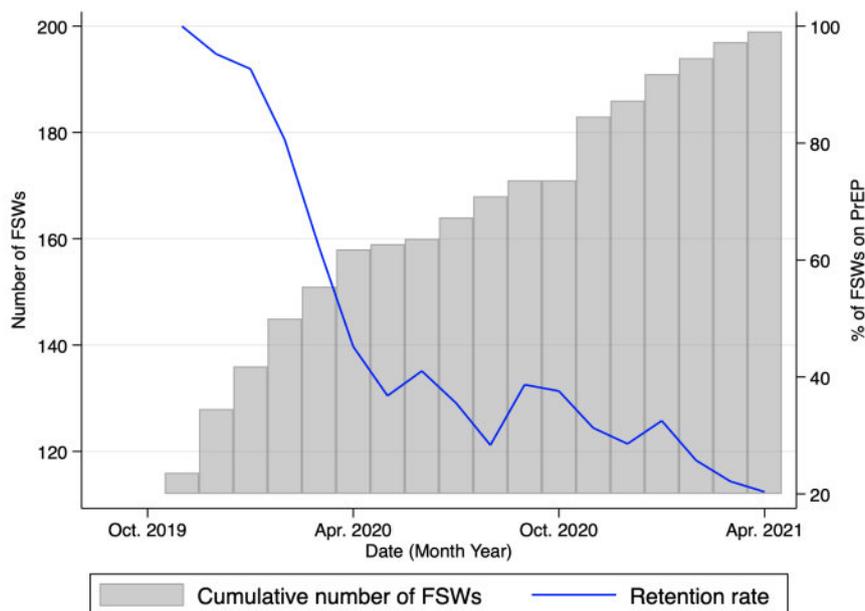
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<sup>16</sup>Doctors report whether or not they presented PrEP to FSWs. They may not present PrEP if a medical emergency overtakes the “script” of the first visit. They may also not report it if the FSW declares not being interested.

<sup>17</sup>Meaning 21% of those who were never prescribed PrEP and 8% of the total sample. Only 74 out of 130 were presented PrEP, while 100% of those who subscribed were presented PrEP.

<sup>18</sup>They represent 15% of those who were never prescribed PrEP. Eventually, 9 of those who were never prescribed PrEP returned for a third visit, among which 6 declared they were interested in PrEP.

Figure 2.2: Monthly sample size and adherence rate



Note: The graph represents the number of FSWs recruited (left y-axis) and the proportion of FSWs on PrEP (right y-axis) per month. A FSW is on PrEP if she has initiated PrEP at least once. The gray bars represent the cumulative number of FSWs recruited each month. The blue line represents the ratio of FSWs who are under treatment (and did not quit) over the cumulative number of participants who initiated PrEP, per month.

Figure 2.2 illustrates a strikingly high rate of attrition. Only 26% out of the 330 FSWs recruited attended the fifth appointment, and on average, they had three medical appointments (see table A2.9). The sample is reduced to HIV-negative participants (330) who were prescribed PrEP at least once (200) to understand treatment adhere. Table 3.2 shows that baseline characteristics of FSWs being prescribed PrEP do not differ from those who were not prescribed.

The primary outcome of adherence depends on FSWs attrition. FSWs have several medical appointments to renew their prescription all along the project. They can be “present”<sup>19</sup>, “late”<sup>20</sup> or “missing”<sup>21</sup>. Since the sample is restricted to FSWs who were prescribed PrEP, the variable equals 0 when FSW is under PrEP (adherent), and it equals 1 if she is no longer under treatment (non-adherent).

<sup>19</sup>The FSW was present on time to renew her prescription.

<sup>20</sup>The appointment has been postponed and the FSW was present to renew her prescription.

<sup>21</sup>The FSW did not show up for the medical appointment and has been missing since then.

## 4.2 Descriptive evidence

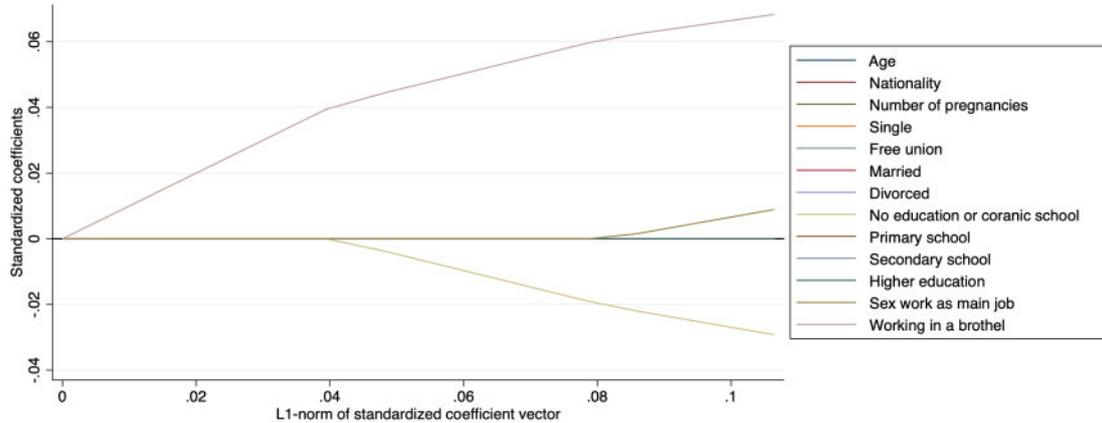
The following section takes advantage of the longitudinal survey to analyse possible confounders of treatment adherence: time-invariant and time-variant determinants of FSWs attrition.

### *Time-invariant determinants*

Tables [A2.5](#) to [A2.13](#) present variables' mean over the sample of FSWs present at each visit rank. The sample size reduces at each round of the survey, illustrating the adherence trend. The table shows that staying in the program is related to time-invariant variables. After five visits, participants have a higher likelihood of leaving the project because they are working less, have another job or are not working in a brothel. The opportunity cost to staying in the study may be smaller when a participant depends less on sex work. Foreign participants, overrepresented in brothels and working more as FSW as main job, are less likely to leave the project. As they are settled in a stable area known for being a sex workplace, they may be more likely to remain in the project and suffer less from stigma. Participants working in the streets are more mobile and more subject to stigma if they are seen in the mobile clinic.

As seen in table [A2.2](#), the longitudinal database provides a high number of correlated variables, which could lead to multicollinearity bias and confounders in the final specification. Some of these variables are time-invariant. In order to better identify those that best determine treatment adherence, I use a non-parametric Lasso regression to complement the stepwise analysis of time-invariant characteristics presented in previous paragraphs. Figure [2.3](#) represents variables selected from the Lasso regression. As a regularized regression, Lasso uses a penalty factor to reduce some coefficients to zero and select relevant features in a large database. FSWs are observed over five rounds of visits. The dependent variable is a discrete variable equals to 1 if the FSW attended the visit, and 0 otherwise. The regression includes time-invariant characteristics and excludes time-variant characteristics to avoid attrition bias. Attrition is positively correlated with working in a brothel, sex work as the main job, and the level of education. The final regressions include these time-invariant characteristics.

Figure 2.3: Lasso-based selection of time-invariant covariates



Note: The graph represents variables selected from the least absolute shrinkage and selection operator (Lasso) regression. Lasso uses a penalty factor to reduce some coefficients to zero and select relevant features in a large database. FSWs are observed over five rounds of visit. The dependent variable is a discrete variable equals to 1 if the FSW attended the visit, and 0 otherwise. The regression includes time-invariant characteristics and excludes time-variant characteristics to avoid the attrition bias. Three variables impact the trajectory: working in a brothel, the sex work being the main job, and never attended school.

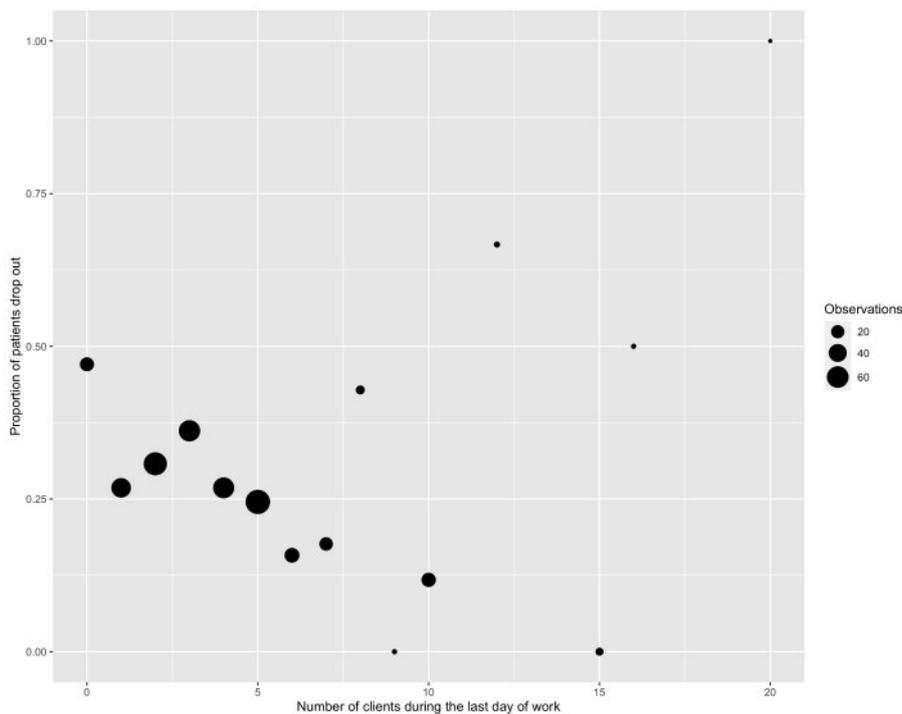
### *Time-variant determinants*

Table A2.4 illustrates the correlation between adherence and time-variant variables with Pearson and Spearman tests of mean variables between rounds. Staying in the project is correlated with characteristics related to the sexual professional activity: condomless intercourse, the price floor, and the number of clients during the last day of work. First, 88.2% to 91.3% of FSWs always used condoms in their intercourse. One would argue that this trend is due to a selection bias in favor of FSWs using more condoms. However, 71% of those attending the fifth visit used condoms at baseline, close to 64.8% of those attending the first visit. Another threat is the underestimation of the number of condomless sexual intercourse (Treibich and Lépine 2019). Doctors interviewed FSWs at the baseline, which reduces the risk of a social desirability bias. Second, FSWs gave their price floor, which significantly decreased at each visit. Again, baseline questions are used to rule out selection bias. The threshold means given at baseline are not different between samples at each round. Eventually, the number of clients measured in follow-up surveys significantly varies at each round. The variable's mean at baseline is not different between samples over each round, which excludes the risk of selection bias.

### *The number of clients*

In figure 2.4, FSWs attrition to the project is negatively correlates with the number of clients. The higher the number of clients, the less likely FSWs would drop out. As attrition is a proxy of treatment non-adherence, figure 2.4 may suggest a negative association between FSWs non-adherence and their number of clients. The number of clients variates between and within individuals, and there is a risk that the continuous recruitment of FSWs may not be random. Figure A2.5 controls for the seasonality of the number of clients. It displays the trend of clients by groups during the recruitment period. The number of clients decreases in the first three months following recruitment, regardless of the recruitment period, dismissing a seasonal effect. Yet, figure A2.4 shows FSWs recruited in November 2019 had five clients on average, while those recruited in April 2021 had three on average. FSWs recruited at the beginning of the project were maybe more exposed to occupational sexual intercourse and the risk of contracting HIV. The final specification will include controls for the date of PrEP initiation.

Figure 2.4: Number of clients and FSWs attrition



Note: The graph represents the proportion of FSWs missing in the project (y-axis) per number of clients (x-axis). Attrition is used as a proxy of treatment non-adherence. Dot size is proportional to the number of observations for each point. Excluding the outliers (smaller dots), the graph suggests a negative relationship between the extensive margin of treatment drop-out and the number of clients.

### 4.3 Non-linear simultaneous equations model

This study tests the hypothesis that sexual intercourse are negatively (positively) associated with treatment non-adherence (adherence). Dropping PrEP could be a rational choice because the return on treatment depends on the risk of contracting HIV during occupational sexual intercourse. However, sexual and adherence behaviors can be simultaneously determined, as underlined in [Quaife et al. \(2018\)](#). The endogeneity issue is tackled with a non-linear simultaneous equations model.

The main outcome,  $Pr(Non-adherence_{i,t})$ , is a latent variable for the treatment drop-out of a participant  $i$  at day  $t$ . Since the sample is restricted to FSWs who are already under treatment, the variable of non-adherence equals 0 when the participant initiates the PrEP and is still under treatment (i.e., pills prescribed are not finished). It takes the value 1 if the participant stops it, i.e. if the treatment is not renewed. To this regard, the treatment adherence measure differs from the treatment compliance definition, which refers to the observance of the daily dosage. This study does not monitor dosage, as it would bias treatment adherence and participation in the study. However, it assumes that compliance is not completely perfect and that participants take 4.75 pills per week instead of 7.<sup>22</sup> Treatment adherence varies over time, but the regression considers the adherence status on the day of the follow-up interview only, when time-varying covariates are available.<sup>23</sup>

Consider the following regression:

$$\begin{aligned} Pr(Non-adherence_{i,t} = 1) = & \Phi(\beta_0 + \beta_1 Number\ of\ clients_{i,t-1} + \\ & \beta_2 \overline{Number\ of\ clients}_i + \beta_3 Health_{i,t-1} + \beta_4 Side\ effects_{i,t-1} + \\ & \beta_5 Condom_{i,t-1} + \beta_6 X'_{i,t} + \lambda_i + \varepsilon_{i,t}) \end{aligned} \quad (2.8)$$

Where  $\Phi$  is the cumulative distribution function of a standard normal distribution.  $X'$  includes a set of participants' earlier characteristics, like age, nationality,

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<sup>22</sup>This hypothesis is based on qualitative survey showing that some FSWs do not take PrEP everyday. It could overestimate the delay before treatment drop-out, but not the coefficient of the impact of the number of clients on the treatment drop-out. As it is somewhat arbitrary, a sensitivity test sets the compliance level at 5.5 pills per week.

<sup>23</sup>Actually, it considers the adherence status on the day before the follow-up interview since the adherence status always equals 0 on the appointment day which was often the same day for the survey interview.

education, days since the first prescription, the number of STD/STI clinical symptoms, and whether sex work is the main job. The explanatory variable of interest is the lagged variable (at  $t - 1$ ) of the *number of clients*, that the FSW had on the previous day (prior to the interview) or the last day of work. *Health* is measured by individual HIV status. It equals 1 if sero-negative, and 0 otherwise. No seroconversion happened among participants who were prescribed PrEP. *Side effects* is any PrEP-related secondary effect declared by participants, such as headaches, dizziness, acne, vomiting... Only twelve events of secondary effects were reported, among which only two were considered “important” enough to stop the treatment. Eventually the regression controls for the use of *Condom* at  $t - 1$ .

Extra-binomial variation, or overdispersion, threatens the specification because of possible omitted covariates, and “the outcome of interest is a series of correlated binary responses” (Gibbons, 1994). The value of  $Pr(Non-adherence)$  is correlated with passed values  $Pr(Non-adherence)$  within FSWs. The extra-binomial variation would underestimate the standard errors and bias the final coefficients. To control for extra-binomial variation, the non-linear equation includes a random effect,  $\lambda_i$ . One hypothesis of the random effect is that covariates are not correlated with unobserved variables. To relax this assumption, the random effect is augmented with the individual mean of the number of clients ( $\overline{Number\ of\ clients}$ ) following the Mundlak procedure (Mundlak 1978).

The non-linear regression cannot include a fixed effect, although *non - adherence* might be correlated with individual unobservable characteristics. First, a fixed effect would assume all measurements are independent and underestimate standard errors. Second, the small sample is subject to the incidental parameter bias.

The relationship between  $Non-adherence_{i,t}$  and  $Number\ of\ clients_{i,t-1}$  is threatened by reverse causality. Participants can use PrEP to increase their condomless sex supply and their number of clients and benefit from a risk premium (Quaife et al. 2018). The second equation of the model describes the function for the *number of clients* hereafter.

The *number of clients* is a continuous variable measuring the number of clients

that FSWs had on the previous day or the last day of work. It depends on the price per sex act. Two prices were available in the database: the price of the last intercourse and the price floor (common price). Unlike the former, the latter is available at every round (see table A2.14). While the price floor is established at XFA1,452<sup>24</sup>, the average price of the last intercourse is around XFA2,435.<sup>25</sup> Although the price floor varies poorly (see figure A2.6), it is correlated with FSWs' attrition (table A2.9).

The *number of clients* depends on the sex work site too. FSWs in brothels can work all day long, unlike those working in streets or hostels, who prefer night work hours. The database gives FSWs displacement history. The model captures the workplace with a categorical variable specifying the workplace name. Sex supply could also decrease if FSWs suffer from inconvenience due to STD/STI symptoms, which is included in the model. Eventually, the *number of clients* depends on the possibility to use *Condoms*, unobservable time-invariant characteristics  $\delta_i$ , the rank of the follow-up survey  $t$ , and days since the first prescription *Days*. Considering those elements, the model for the *number of clients* is:

$$\begin{aligned} \text{Number of clients}_{i,t} = & \alpha_0 + \alpha_1 \text{Non-adherence}_{i,t} + \alpha_2 \text{Price}_{i,t} + \\ & \alpha_3 \text{Workplace}_{i,t} + \alpha_4 \text{STD}_{i,t} + \alpha_5 \text{Condom}_{i,t} + \alpha_6 \text{Days}_{i,t} + \delta_i + \varepsilon_{i,t} \end{aligned} \quad (2.9)$$

The system of equations should meet the order and rank conditions to be solved with a simultaneous equations model (Wooldridge 2010, 2015). The first condition states that each equation shall be overidentified, meaning they shall have at least one exogenous variable that is not in the other equation. *Price* and *Workplace* are exogenous variables from equation 2.9 that are not part of equation 2.8. The *Workplace* sets as an instrumental variable for the *Number of clients*. The second condition states that at least one of the exogenous variables' coefficients in equation 2.9, that is not included in equation 2.8, must be non-zero. This condition is met with the *Workplace*, that is significantly impacting the number of clients (see

<sup>24</sup>Around US \$1.80.

<sup>25</sup>The price of the last intercourse is highly skewed thus I winsorized the variable to 99.5%. All prices above XFA10,000 are reduced to XFA10,000.

Figure A2.9). As a result, the simultaneous non-linear equations system is:

$$\begin{cases} Non-adherence_{i,t} = \beta_0 + \beta_1 Number\ of\ clients_{i,t-1} + \beta_2 \overline{Number\ of\ clients}_i + \\ \beta_3 Health_{i,t-1} + \beta_4 Side\ effects_{i,t-1} + \beta_5 Condom_{i,t-1} + \beta_6 X'_{i,t} + \varepsilon_{1,i,t} \\ Number\ of\ clients_{i,t} = \alpha_0 + \alpha_1 Non-adherence_{i,t} + \alpha_2 Price_{i,t} + \alpha_3 Workplace_{i,t} + \\ \alpha_4 STD_{i,t} + \alpha_5 Condom_{i,t} + \alpha_6 Days_{i,t} + \delta_i + \varepsilon_{2,i,t} \end{cases} \quad (2.10)$$

The reduced form of the adherence equation incorporates the number of clients in  $t - 1$  as lagged variables are considered exogenous variables, while the reduced form of the number of clients in  $t$  takes into account the adherence status at  $t$ . The  $Non-adherence_{i,t}$  regression is a probit without random effect, despite the specification presented in equation 2.8, but with Mundlak control (individual mean of the number of clients). Indeed, the simultaneous equation model cannot include random effects in the non-linear regression because of the individual fixed effect in the linear regression. Random effects are assumed to be uncorrelated with the other regressors, normally distributed across groups, and not individually identified. Fixed effects are individually identified and can be correlated with the other variables. Error terms are composed of unobserved individual-specific effects  $\eta_i$  and time-specific events  $\nu_{i,t}$ , there could be a correlation among error terms of both  $Non-adherence$  and  $Number\ of\ clients$  ( $\varepsilon_{1,i,t}$  and  $\varepsilon_{2,i,t}$ ).

$$\begin{cases} \varepsilon_{1,i,t} = \eta_{1,i} + \nu_{1,i,t} \\ \varepsilon_{2,i,t} = \eta_{2,i} + \nu_{2,i,t} \end{cases} \quad (2.11)$$

That gives the following variance-covariance matrix for individual effects:

$$\Sigma_{\eta} = \begin{pmatrix} \sigma_{\eta,1}^2 & \sigma_{\eta,1,2} \\ \sigma_{\eta,1,2} & \sigma_{\eta,2}^2 \end{pmatrix} \quad (2.12)$$

The variance-covariance matrix for time errors is:

$$\Sigma_{\nu} = \begin{pmatrix} \sigma_{\nu,1}^2 & \sigma_{\nu,1,2} \\ \sigma_{\nu,1,2} & \sigma_{\nu,2}^2 \end{pmatrix} \quad (2.13)$$

The system is estimated by a Full Information Maximum Likelihood thanks to the Stata command *cmp* (Roodman 2011). It allows to get parameter even with missing data, as it is the case for some observations in this database. It takes

into account possible correlations among errors  $\varepsilon_{1,i,t}$  and  $\varepsilon_{2,i,t}$  resulting from the simultaneous equations model. It allows simultaneous estimation of non-linear and linear equations.<sup>26</sup>

## 5 Results and discussion

### 5.1 Main results

#### *Basic regressions*

Figure A2.7 presents the coefficient estimates of equation 2.8. The number of clients is negatively associated with the likelihood of treatment drop-out. Having more clients in  $t - 1$  increases (decreases) treatment adherence (drop-out) at  $t$ . The coefficient is stable with a fixed-effects linear probability model whose estimates are presented in figure A2.8. The likelihood of stopping the treatment increases with the number of STI/STD too. Doctors may have prescribed another treatment to diagnosed FSWs and encouraged them to hold PrEP treatment for some time. The fixed effect OLS presented in figure A2.9 shows that the number of clients is driven by the adherence to PrEP, sex work sites, STI/STD symptoms, and the use of condoms.

#### *The simultaneous equations model*

Table 2.2 presents the results of the simultaneous equations model. The top part of the table presents the results of the adherence regression. First, among covariates, treatment drop-out is positively associated with the number of days since the first prescription, using condoms, and being a sex worker as the main job. The coefficients of the two latter variables are surprising. Being a sex worker as the main job is time-invariant. The coefficient is significantly negative, meaning that working mainly as a sex worker decreases the likelihood of treatment adherence. However, table A2.2 shows that women whose sex is the main job worked more in

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<sup>26</sup>An alternative would be to use a non-linear 2SLS equation to instrument the number of sexual encounters that would be endogenous with treatment adherence. Participants could choose to adhere to the treatment to increase the number of intercourse. I exploit port activity, the main source of economic activity in the town of San Pedro, as an instrument for the number of clients. Indeed, the port activity remains the main source of income for the town's inhabitants, and preliminary surveys have shown that the number of clients varies according to the port's activities, notably cocoa exports. The validity of the instrument lies in its strict exogeneity and its strong correlation with the dependent variable. The exclusion restriction condition does not seem to be under threat and captures both supply and demand behavior, while the correlation is well verified.

the last month than those who were not “full-time” sex workers. One should expect that working full-time would increase the number of sexual intercourse, the risk of HIV infection, and then treatment adherence. This result can be understood if women for whom sex work is not the main job are more interested in preventing the risk of HIV infection in their occupational sexual intercourse. They may be more exposed to the risk of HIV infection. The Student test shows that workers whose sex work is not their main job are less likely to use condoms.

In contrast, the price of the last act for FSWs whose sex work is not the main job is significantly higher, although there is no difference in the price floor. The coefficient may be biased if the “part-time” sex workers had come less often but at the right time to renew PrEP.<sup>27</sup> The Student test shows that “part-time” and “full-time” workers had the same number of follow-ups on average. One could expect “part-time” sex workers to be in more stable relationships and adhere more to PrEP to protect their partners. Again, a simple Student test shows no difference in the marital status between the groups. Eventually, the Student test shows that both groups have the same number of clients on average. Yet, “part-time” sex workers work less (see table A2.2). All in all, adherence would be triggered by “part-time” sex workers who seem more productive and have more condomless intercourse.

Second, following the theoretical model, the number of clients is the only parameter empirically impacting treatment adherence. Because there was no seroconversion in this empirical framework, the health status variable is a constant and does not need to appear in the final tables<sup>28</sup>, and the coefficient for side effects is not significant. Figure A2.10 shows that one additional client significantly increases the negative marginal impact on the likelihood of dropping the treatment. Using the definition of primary adherence (see section 1), each additional client decreases the probability of stopping treatment by 1%. The average impact is small but robust to a series of robustness tests. It shows that sex workers are engaged rationally in prevention treatment, confirming the theoretical findings.

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<sup>27</sup>In other words, they would have had fewer follow-ups, but each follow-up would have been done in time to renew PrEP.

<sup>28</sup>The only known comparable database did not find seroconversion either (TAPS from [Eakle et al. \(2017\)](#)).

The second part of table 2.2 shows that treatment (non-) adherence affects the number of clients. Being under PrEP increases the number of clients, in line with the results presented in Quaife et al. (2018). Using condoms increases the number of clients too. FSWs may protect themselves knowing that the number of occupational sexual partners is associated with a higher risk of HIV infection. More information on the demand side is needed to deepen the analysis of this coefficient. The variation in sex work sites is the other main determinant, changing the number of clients up to 8.

In the bottom part of table 2.2,  $\text{atanh } \rho_{12}$  highlights several simultaneity issues. The correlation coefficient between unobserved components is significant and positive, which validates the relevance of using a simultaneous equations model. The coefficient of  $\ln \sigma$  shows that unobserved FSWs characteristics significantly impact treatment adherence. This is consistent with tailoring the treatment based on the heterogeneous characteristics of sex workers, specifically their heterogeneous position in the sex market.

Table 2.2: simultaneous equations model

	Simultaneous equations	
	Coeff.	SE
<b>Non-adherence (=1 if dropout)</b>		
Number of clients (t-1)	-0.161***	(0.0541)
Individual mean Number of clients	0.121*	(0.0669)
Age	-0.0223	(0.0174)
Nationality (=1 if ivoirienne)	0.296	(0.306)
Education: None	0	(.)
Primary	-0.0992	(0.257)
Secondary	0.0392	(0.359)
Higher	0.202	(0.528)
Side effects (t-1)	0.0211	(0.672)
Number of STD/STI symptoms (t-1)	0	(.)
Use condom in the last intercourse (t-1)	0.531**	(0.227)
Main job: sex worker	0.511**	(0.257)
Days since first prescription	0.00852***	(0.000923)
Constant	-1.791**	(0.792)
<b>Number of clients</b>		
Non-adherence (=1 if dropout)	-1.980**	(0.7822)
Price of sexual intercourse	0.000729***	(0.000135)
Sex work site: AD	0	(.)
AN	8.028***	(1.441)
BE	-2.450***	(0.738)
DO	3.295***	(0.809)
GA	2.654*	(1.586)
LB	-1.930	(1.809)
MO	-0.310	(1.275)
PO	2.828**	(1.328)
SE	-6.234***	(2.025)
TR	-4.097***	(1.559)
WA	-0.281	(1.386)
Number of STD/STI symptoms	0.135	(0.423)
Use condom in the last intercourse	1.152**	(0.529)
Days since first prescription	0.0122	(0.00751)
Constant	-2.031	(1.741)
$\ln \sigma_2$	0.759**	(0.359)
$\operatorname{atanh} \rho_{1,2}$	2.182***	(0.377)
Observations	401	

Note: \*\*\* p <.01, \*\*p <.05, \* p <.1 Standard errors are in parenthesis. The table presents the result of a simultaneous non-linear equation model. The simultaneous equations model includes a non-linear and a linear equations. The non-linear equation is a probit with Mundlak specification. The main outcome is *Non-adherence* and the Mundlak specification is for the independent variable of interest, i.e. the individual mean for the number of clients. The linear equation is a fixed effect OLS of the *Number of clients*. It includes fixed effect at individual level. Both equations include a set of covariates described in section 4.3. Despite the specification presented in Figure A2.7, the simultaneous equations model cannot include random effect in the non-linear regression because of the individual fixed effect in the linear regression. Random effects are assumed to be uncorrelated with the other regressors, and are not individually identified, and assumed to have values that are normally distributed across groups. Fixed effects are individually identified and can be correlated with the other variables. In the bottom part of the table,  $\sigma$  and  $\rho$  represent  $\eta$  (see subsection 4.3). Specifically,  $\sigma$  is the standard deviation parameter for the error and  $\rho$  is the correlation coefficient for each pair. The parameters are unbounded with logarithm and arc-hyperbolic tangent transformations, respectively.

*Unobserved heterogeneity*

Different hypotheses are explored to identify unobserved characteristics. First, in the theoretical model, treatment efficiency,  $k$ , moderates the impact of sexual intercourse  $s$ . The respect of the daily posology could measure PrEP efficiency but it is not available in this database (see section 3). In addition, treatment effectiveness has become subjective because of information asymmetries about the objective treatment effectiveness. Patients rely on information their physician shares about the effectiveness of preventive treatment. As such, beliefs in treatment efficiency can impact treatment adherence. From the first follow-up, the survey asks FSWs about their belief in the effectiveness of treatment for HIV. However, there was 86% non-answer to this question. I rather take advantage of the panel structure of the database to adopt a semi-parametric method for the heterogeneity analysis. Figure A2.11 presents the results of a Cox regression model that computes the hazard ratio to drop the treatment at a particular point in time between two groups<sup>29</sup>: those who believed and did not believe in PrEP efficiency. The Cox regression model is a semi-parametric model to fit regression for survival analysis. Let consider:

$$h(t) = h_0(t) \times \exp(\beta_1 X'_i + \beta_2 Belief_i)$$

where  $t$  is the survival time;  $h(t)$  is the hazard of treatment drop-out;  $X'_i$  the covariates including the number of clients, the age, the nationality, health, side effect, the main job, working on a brothel, use of condoms on the previous day;  $h_0(t)$  is the baseline hazard, i.e. the value of the hazard if all  $x_i$  are equal to zero;  $Belief_i$  that equals 1 if they believe in the treatment efficacy. Figure A2.11 suggests that patients who believe less in treatment efficiency have a lower survival time in treatment compared to those who believe in it.

Second, heterogeneity in treatment adherence could be related to FSWs' mobility. Nearly 24% and 20% of FSWs recruited moved within and outside San Pedro, respectively (see Figures A2.14 and A2.15). FSWs usually move to optimize their work opportunities, captured by the number of clients. Adherence could be im-

<sup>29</sup>“The hazard ratio is interpreted as the instantaneous rate of occurrence of the event of interest in those who are still at risk for the event. It is not a risk, though it is commonly interpreted as such.” (Rich et al. 2010)

pacted by FSWs' mobility since the treatment is available in San Pedro only. FSWs were able to ask for prescriptions to cover the period of their leave. The second equation controls the sex work site at  $t$ , but the survey did not monitor FSWs who went away and did not return. FSWs working in a brothel are less likely to move away because they usually leave there and have a core local demand and a lower opportunity cost than those working in hotels or at home, among other reasons.

## 5.2 Discussion

The results show that the number of clients is negatively associated with treatment non-adherence. The error term being positive means that there are unobservable variables. Different sensitivity tests assess the stability of the estimates.

First, this study looks at primary adherence, i.e., whether the patient is engaged in treatment. Measuring secondary adherence would be needed to measure sex workers' adherence to daily medical posology. Understanding patients' primary adherence is as critical as secondary adherence to the successful implementation of public policy. FSWs could commit to a specific time frame for treatment and be monitored for adherence (creatinine level or pill counts), which would encourage them to adhere. Patients could also declare their treatment intake afterward, but this would lead to the same bias as the one identified at the beginning of the study, which justified the use of attrition as an outcome. FSWs were prescribed treatment for one month. In the baseline model, I assume that FSWs will not take the drug every day as recommended. The compliance level is set at 4.75 pills per week. With this assumption, a FSW is considered to have stopped treatment after 45 days instead of 30 days, if she does not come back to renew her prescription. This gives her a little more time to come back and ask for a new prescription than would be the case with a strict application of the dosage. I changed the level of compliance to be closer to what is expected, at 5.5 pills per week. Table [A2.15](#) presents the results of the simultaneous equations model. Estimates are still negative and significant.

The residuals of *adherence* and *number of clients* are likely correlated within sex work sites. Table [A2.16](#) presents results with standard errors clustered at the sex work sites level to control for within-unit correlation. The coefficient of

the *number of clients* is still negative and significant, unlike the coefficient of *adherence* in the second equation, that is not significant anymore.

Third, some FSWs left the program after one follow-up, which could bias the Mundlak specification. The sample is restricted to individuals surveyed at least three times to overcome this issue. Coefficients presented in table A2.17 do not change with a sample reduced to 113 participants. One could suggest replicating the simultaneous equations model using the mean at the sex work site level with the same sample size. Figure A2.12 shows that the Kernel density of the individual mean has more variation than the sex work sites mean, specifically at the end of the distribution. Table A2.18 presents the estimation with the Mundlak procedure at sex work sites. The *adherence* coefficient in the second equation is high, and the sign of the constant has changed to positive. Using the mean at the work site level may be noisier than the mean at the individual level.

Further, the definition of the outcome variable can also be discussed. The choice to observe non-adherence is a result of the sample selection. The sample for the main regression is restricted to FSWs who received a prescription. Indeed, nearly every FSWs who were introduced to but never took the pill (measured by attrition) were not surveyed in the follow-ups. I only have the baseline interview for them. It can be considered important to document non-adherence after the first visit as well. Thus, the following equation where  $Adherence = 1$ . The sample includes the 271 FSWs who were introduced to PrEP:

$$\left\{ \begin{array}{l} Adherence_{i,t} = \beta_0 + \beta_1 Number\ of\ clients_{i,t-1} + \beta_2 \overline{Number\ of\ clients}_i + \\ \beta_3 Health_{i,t-1} + \beta_4 Side\ effects_{i,t-1} + \beta_5 Condom_{i,t-1} + \beta_6 Marital_i + \beta_7 X'_{i,t} + \varepsilon_{1,i,t} \\ Number\ of\ clients_{i,t} = \alpha_0 + \alpha_1 Adherence_{i,t} + \alpha_2 Price_{i,t} + \alpha_3 Workplace_{i,t} + \\ \alpha_4 STD_{i,t} + \alpha_5 Condom_{i,t} + \alpha_6 Days_{i,t} + \delta_i + \varepsilon_{2,i,t} \end{array} \right. \quad (2.14)$$

As there is no variation in  $Adherence_{i,t}$  for FSWs who did not come back after

the baseline, most of them are dropped for the final estimation by Stata software. Table A2.20 shows that adherence to PrEP treatment is positively associated with the number of clients. Conversely, the number of clients is positively associated with adherence to PrEP.

Additionally, marital status probably impacts sex workers' work and access to treatment through different channels (Biomndo et al. 2021, Duff et al. 2016, Angelucci and Bennett 2021, Greenwood et al. 2017). Table A2.19 presents estimates with marital status as a control variable in the *Non-Adherence* equation of the simultaneous equations model, as the individual-fixed effects of the second equation control for marital status already. The variable *Marital* equals 1 if the FSW has a partner. Results hold to this new estimation.

Another threat would be the non-respect of the condition of exclusion restriction with the instrumental variable. The condition states that the instrumental variable, i.e. the *sex work sites*, should not be correlated with the outcome of the second stage regression, i.e. *treatment adherence*. The lasso regression excluded the sex work sites from the selection of covariates in figure 2.3. Additionally, figure A2.13 presents the coefficients from the first stage regression with sex work sites added as a covariate. It shows no significant impact of sex work sites on adherence.

Further, the theoretical model uses the number of occupational sexual intercourses proxied by the number of clients to capture the impact of risky sex on health. As such, it assumes that all professional sexual intercourses have the same level of risk. It would be interesting to discuss this, particularly how relaxing this assumption might affect the implications. Yet, not using a condom increases the risk of contracting HIV. The identification strategy adds a control variable for condom use. Ideally, one could expect a simultaneous equations model including a third equation for condom use. However, measuring condom use and the factors of variation is subject to various biases, and the database used is not designed to overcome these biases. It is the FSW's answer to "Did you use a condom the last time you had sex?" This questionnaire, like other declarative methods, is affected by social desirability bias and sex workers tend to overestimate condom

use (Treibich and Lépine 2019). Moreover, estimating the variation in condom use needs time-varying explanatory variables. The database should provide variables related to the income of sex workers and their relatives (Robinson and Yeh 2011) and on whether the client requested unprotected intercourse. Unfortunately, I do not have such information. To our knowledge, the best methodology to measure condom use is through a daily logbook, as did Robinson and Yeh (2011).

Despite efforts to address econometric challenges, some limitations remain associated with the structure of the survey. One concern would be that the number of clients is declared, and FSWs could misreport the real number. The risk of social desirability is reduced by unconditional access to drugs and the presence of peer educators and doctors. Besides, variables other than the *number of clients*, such as the number of condomless sexual intercourse cases, could better measure the theoretical parameter of *sexual risk*. The use of condoms is preferred as a control for condomless sexual intercourse, as it may be more threaten by social desirability bias (Treibich and Lépine 2019) or the error of measure. Indeed, the question raised for the condom use screens sexual behavior over the past 6 months, and participants answer whether they use it “Always, Often, Sometimes, or Never.”

Subjective measures of *sexual risks* could complement the empirical analysis too. Perceived risk of contracting HIV drives the decision to adhere to preventive health behavior. Unfortunately, the available variables do not allow an accurate measure of the subjective estimate of the risk of contracting HIV at each sexual encounter.

Eventually, ideally, a correlated random effect model (CREM) would measure heterogeneous return in treatment adherence, as in Suri (2011). The Mundlak procedure used in the baseline regression is one of many different approaches in correlated random coefficient models to control for the heterogeneity in the cost-benefit analysis of technology adoption (here the treatment adherence). It allows researchers to estimate individuals' comparative advantage in the adoption decision and the distribution of the rate of return. The model would be adapted to the discrete variable for adherence and the unbalanced structure of the sample with

a non-linear correlated random effect model for unbalanced database, thanks to programming innovation in Stata ([Wooldridge 2019](#), [Albarran et al. 2019](#)). With the same database, it would mean including a variable granular enough to measure the return on technology adoption, such as a daily diary with the number of work hours, the type of sexual services and their specific prices. The risk of a diary is that it should improve the productivity of sexual activity and therefore impacts the risk of contracting HIV. New data sets can be collected to improve these results.

## 6 Conclusion

This paper attempts to establish a causal link between heterogeneity in a cost-benefit analysis and the decision to adhere to HIV preventive treatment. Specifically, the objective is to know if the risk of contracting HIV reduces or increases the probability of adopting PrEP preventive treatment. As this risk varies with occupational sexual risks, the latter is included as a new parameter in stylized theoretical facts, inspired by [Lamiraud and Geoffard \(2007\)](#). The theoretical framework predicts an increase (decrease) in (non)adherence to preventive treatment when the risk of contracting HIV increases (decreases).

The second part tests these results using a novel database collected from female sex workers in Côte d'Ivoire between November 2019 and April 2021. I exploit the longitudinal database by measuring PrEP non-adherence with attrition and the risk of HIV infection with the number of clients. Using the simultaneous equations model, I am trying to tackle the reverse causality bias between the number of occupational sex acts and non-adherence. The results show that the probability of dropping out of treatment decreases by 1% for each additional client. Although the impact is small, it is robust to various sensitivity tests. These results enrich early research concerns about risk compensation behavior among FSWs when introducing PrEP. The results suggest that FSWs would be rational in their investment in preventive health.

This analysis questions adherence to preventive treatment beyond FSWs. Adopt-

ing a medical technology requires personal involvement that varies according to various parameters that are sometimes omitted in policy recommendations. In terms of WHO recommendations for PrEP, better data sets are needed to complement these findings and measure heterogeneity for treatment adherence.

## Appendix A2. Chapter 2

### Theoretical framework

We note  $h$  the patient's health status;  $q$  the level of well-being;  $k$  the benefits of the treatment on one's health status;  $c$  the negative side effects on well-being; and  $s$  the number of sexual intercourse. We make the assumption that  $u_h > 0$ ,  $u_q > 0$ ,  $u_{hh} < 0$ ,  $u_{qq} < 0$  et  $u_{hq} = u_{qh} \geq 0$ . We know that the health status is  $h' = h + \frac{s}{1+k\theta}$  and the well-being is  $q' = q - c\theta$ .

We know that the threshold is defined by the equation:

$$\Delta(k, c; h, q, s) = u\left(h - \frac{s}{1+k}, q - c\right) - u(h - s, q) = 0 \quad (\text{A2.1})$$

Following section 3, we know that :

$$\Delta_k = \frac{s}{1+k^2} u_h\left(h - \frac{s}{1+k}, q - c\right) \geq 0 \quad (\text{A2.2})$$

The threshold  $k$  increases with  $c$ . Proof:

Based on the Implicit function theorem (IFT),

$$k_c = \frac{-\Delta_k}{\Delta_c} \quad (\text{A2.3})$$

And since by assumption  $u_q > 0$ ,

$$\Delta_c = -u_q < 0 \quad (\text{A2.4})$$

So based on eq. A2.2 and A2.4:

$$k_c = \frac{-\Delta_k}{\Delta_c} > 0 \quad (\text{A2.5})$$

The threshold  $k$  increases with  $h$ . Proof:

Based on the IFT,

$$k_h = \frac{-\Delta_k}{\Delta_h} \quad (\text{A2.6})$$

and since by assumption  $u_{hh} < 0$ ,

$$u_h(h - s, q - c) \geq u_h\left(h - \frac{s}{1+k}, q - c\right) \quad (\text{A2.7})$$

Then,

$$\Delta_h = u_h\left(h - \frac{s}{1+k}, q - c\right) - u_h(h - s, q) \leq u_h(h - s, q - c) - u_h(h - s, q) \quad (\text{A2.8})$$

Additionally, by assumption  $u_{hq} \geq 0$  and because  $q - c < q$ , so

$$\Delta_h \leq 0 \quad (\text{A2.9})$$

Therefore, based on eq. [A2.2](#) and [A2.9](#):

$$k_h = \frac{-\Delta_k}{\Delta_h} > 0 \quad (\text{A2.10})$$

The threshold  $k$  decreases with  $q$ . Proof:

Based on the IFT,

$$k_q = \frac{-\Delta_k}{\Delta_q} \quad (\text{A2.11})$$

And since the assumption is  $u_{qh} \geq 0$  then,

$$\Delta_q = u_q\left(h - \frac{s}{1+k}, q - c\right) - u_q(h - s, q) \geq u_q(h - s, q - c) - u_q(h - s, q) \quad (\text{A2.12})$$

And since  $u_{qq} < 0$  then,

$$\Delta_q \geq 0 \quad (\text{A2.13})$$

Therefore, based on eq. A2.2 and A2.13:

$$k_q = \frac{-\Delta_k}{\Delta_q} < 0 \quad (\text{A2.14})$$

## Setting

[PRINCESSE ANRS 12381](#) aims to “develop, document, and analyze a community-based care package combining testing, combination prevention, including pre-exposure prophylaxis (PrEP), immediate HIV treatment, hepatitis B management, and sexual and reproductive health (SRH) in order to reduce HIV exposure among female sex workers (FSWs) and their partners in Côte d'Ivoire”. It is carried by the CEPED - Centre Population et Développement de l'Université Paris Descartes et de l'Institut pour la Recherche et le Développement à Paris and PAC-CI - Site de l'Agence nationale de recherches sur le Sida et les hépatites virales - Laboratoire international associé de l'Inserm à Abidjan. Is it funded by the ANRS CEPED : Agence Nationale de la Recherche sur le Sida et les Hépatites Virales. It follows a pilot project on pre-exposure prophylaxis treatment (PrEP-CI ANRS 12361) that revealed a high HIV rate among FSWs in the city of San Pedro.

I joined the multidisciplinary project that gathers epidemiologists, demographers, sociologists, and doctors in June 2019. I proposed bringing an economic angle to the question of PrEP uptake to complement the descriptive analysis. My dissertation approach to preventive health behaviors met the project's interest in understanding the health behaviors of FSWs.

Although most of the project was already set, I had to design my research component. In 2019, the randomized control trial was the gold standard of causality inferences because of its contributions to anti-poverty research and was awarded the Nobel Prize. However, it soon became difficult to pursue experimentation with a control group of FSWs for an incentive to encourage or discourage the adoption of HIV prevention treatment. FSWs' occupation questions their relationship to consent daily. Any RCT for this specific question with this specific setting would have fallen into the three situations where an “individual is unable to make a rational assessment of the risk” ([Glennester and Powers 2016](#)). First, following the 1978 Belmont ethical framework, FSWs participants are vulnerable. Second, the physical and psychological medical risks outweighed the scientific benefits of health behavior. Third, the inducement to access exclusive HIV preventive treatment seemed so high that it could have undermined the ability of FSWs to make a

rational decision about risks and benefits. In this regard, PRINCESSE project set an invariable rule of consent: FSWs could withdraw their consent and leave at any moment.

My first research design would take advantage of the random displacement of the medical truck. However, the Covid-19 pandemic increased the mobility of FSWs and reduced the desired sample size from 500 to 350. Eventually, I decided to take advantage of the consent rule in the final research design for this study.

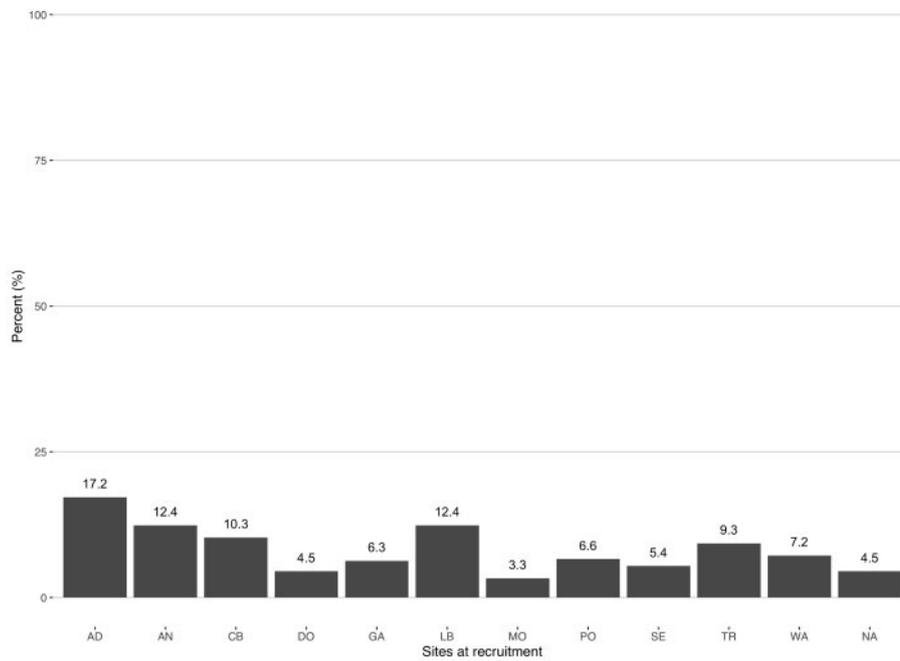
I carried out two surveys before the global lockdown. First, I assisted an anthropologist in a qualitative survey with a dozen sex workers in December 2019. Second, I conducted a pilot survey with 34 FSWs in February 2020. Collaborating with the investigators, I prepared a survey with four components: socio-demographic characteristics, health, income, and market. Although the sample size was small, the descriptive analyses identified structural parameters of the San Pedro sex market and stylized facts about FSWs' prevention behavior. The results help the adjustment of the follow-up survey.

Table A2.1: Descriptive summary split by prescription groups

	All N=271	Not prescribed N=74	Prescribed N=197	2*p-value	2* N
Age	30.0 (7.09)	28.7 (7.13)	30.4 (7.04)	0.085	271
Nationality (Ivorian)	0.58 (0.49)	0.55 (0.50)	0.59 (0.49)	0.610	271
Level of education					
NA	0.35 (0.48)	0.32 (0.47)	0.36 (0.48)	0.516	269
Never went to school or Coranic school	0.01 (0.11)	0.04 (0.20)	0.00 (0.00)	0.083	269
Primary school	0.32 (0.47)	0.27 (0.45)	0.34 (0.48)	0.280	269
Secondary school	0.26 (0.44)	0.32 (0.47)	0.24 (0.43)	0.266	269
Higher education	0.06 (0.23)	0.05 (0.23)	0.06 (0.23)	0.966	269
Sex work as main job	0.49 (0.50)	0.49 (0.50)	0.49 (0.50)	0.932	271
Work everyday last month	0.92 (0.27)	0.90 (0.30)	0.93 (0.26)	0.500	267
Years of experience	3.60 (4.25)	2.80 (3.15)	3.89 (4.56)	0.029	266
Works in a brothel	0.48 (0.50)	0.50 (0.50)	0.48 (0.50)	0.739	271
Had condomless intercourse (baseline)	0.71 (6.02)	1.68 (11.5)	0.35 (0.48)	0.323	270
Number of clients (baseline)	4.49 (2.86)	3.80 (1.93)	4.72 (3.08)	0.008	234
Threshold price (baseline)	1636 (843)	1683 (993)	1619 (787)	0.648	245
Was interested in PrEP	0.99 (0.09)	0.97 (0.16)	1.00 (0.00)	0.159	271

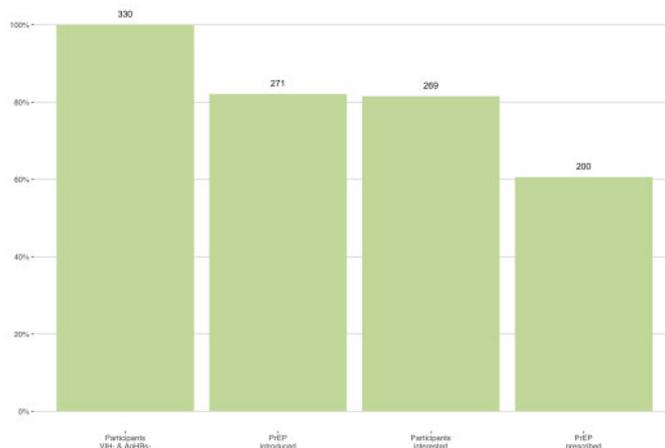
Note: The table presents summary statistics among FSWs who were introduced at least once to PrEP. The columns "All", "Not prescribed", "Prescribed" presents mean and standard deviations in brackets of three groups: the full sample, those who were prescribed PrEP and those who were not prescribed PrEP. The p-value is computed from the Pearson test when row-variable is normal and from the Spearman test when it is continuous non-normal. If the row-variable is categorical, the p-value for trend is computed from Mantel-Haenszel test of trend. The last column gives the total number of observations available for each variable.

Figure A2.1: Recruitment and sex work sites



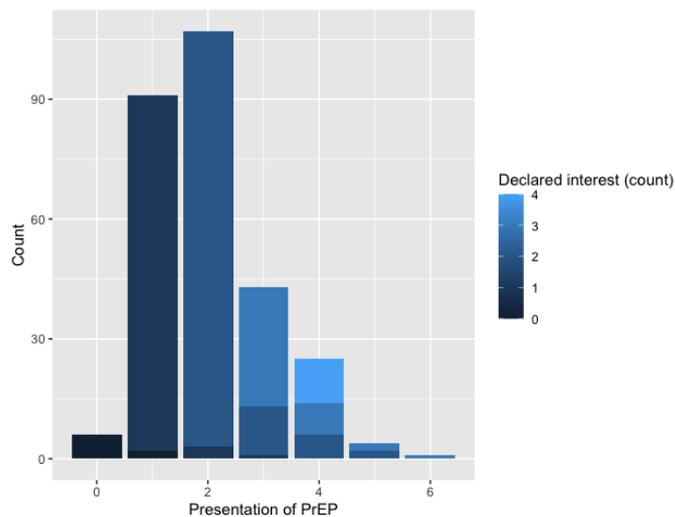
Note: The graph represents the proportion of FTs from each sex work site at the time of recruitment. FSWs were recruited on various 12 sex work sites in the city of San Pedro and its suburb. One sex work site (MO) was dropped after a month because of bad road access, that hampered the regularity of the medical visits. This site was replaced by another one.

Figure A2.2: Sample size for analysis



Note: The graph represents the sample from recruitment into the Princess program to the initiation of PrEP (first prescription of the drug). In the first stage, all women over 18 who identify as sex workers can join the program if they agree. At recruitment appointments, FSWs are screened for HIV and introduced to PrEP. Two weeks later, FSWs receive their HIV test results. If they are negative, doctors formally ask if they are interested in taking PrEP and give their consent. If they say they are interested, then the doctors prescribe PrEP.

Figure A2.3: Presentation and interest in PrEP



Note: The graph represents the ratio between the number of times FSWs expressed interest and the number of times they were introduced to PrEP. Doctors presented PrEP multiple times if FSWs had several weeks without treatment. The doctor decided when the number of weeks without treatment was long enough to represent PrEP, usually more than a month without any medical visits. The likelihood of refusing PrEP at least once increased with the number of times PrEP was presented. FSWs who were presented with PrEP twice were more likely to accept it each time than those who were presented with PrEP three or four times.

Table A2.2: Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Age									
(2) Nationality (Ivoirienne)	-0.07								
(3) Sex work as main job	0.04	-0.23***							
(4) Working in a brothel	0.14**	-0.15**	0.11						
(5) Experience as sex worker (years)	0.49***	-0.08	-0.01	0.01					
(6) Work everyday last month	0.07	-0.25***	0.25***	0.11	0.04				
(7) Number of pregnancies	0.37***	0.10	-0.17**	-0.06	0.14	-0.06			
(8) One condomless sexual intercourse during the last 7 days	-0.13	0.25***	-0.13	-0.21***	-0.03	-0.21***	-0.06		
(9) HIV positive	0.30***	0.02	0.03	0.16**	0.02	0.02	0.06	-0.22***	
(10) Stopped PrEP (documented)	-0.04	-0.20***	0.02	0.16**	0.04	0.06	-0.08	0.10	-0.01

Note: Correlation matrix between FSWs' socio-demographic characteristics using Pearson method of the main characteristics of the FSWs. \*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .1$ . The sample is restricted to FSWs under treatment. The variable "Stopped PrEP (documented)" refers to situations where FSW and/or the physician have stopped PrEP, which is different from program attrition.

Table A2.3: Background characteristics at baseline

Statistic	Mean	St. Dev.	N
DEMOGRAPHIC			
Age	30.72	7.88	330
Nationality (Ivoirienne)	0.58	0.49	330
Number of pregnancies	3.10	2.21	146
<i>Marital status</i>			153
Single	0.46		
Free union	0.46		
Married	0.01		
Divorced / Separated	0.03		
Widow	0.03		
<i>Education</i>			327
Never went to school	0.34		
Coranic school or primary school	0.35		
Secondary school	0.26		
Higher education	0.05		
LABOUR			
Sex work as main job	0.48	0.50	330
Experience as sex worker (years)	3.74	4.29	323
Working in a brothel	0.51	0.50	330
Work everyday last month	0.92	0.27	325
One condomless sexual intercourse during the last 7 days	0.32	0.47	328
SEXUAL HEALTH			
HIV positive	0.13	0.34	323
STD/STI symptoms	0.18	0.39	214

Note: Descriptive statistics of the main characteristics of the FSWs. All but marriage, education and STI variables were asked at the baseline, during the recruitment. Data collected at baseline give the average across participants.

Table A2.4: Summary descriptives table by groups of 'Rank of the visit' (FSWs that received PrEP)

	1	2	3	4	5	2* p-value	2* N
	N=200	N=181	N=133	N=91	N=70		
Age	30.4 (6.99)	30.7 (7.04)	31.1 (7.30)	31.5 (6.73)	31.0 (7.09)	0.758	675
Nationality (Ivoirienne)	0.60 (0.49)	0.56 (0.50)	0.53 (0.50)	0.49 (0.50)	0.43 (0.50)	0.132	675
Level of education:						.	670
Never went to school	35.7%	35.0%	32.6%	30.0%	24.6%		
Primary school	34.7%	34.4%	33.3%	35.6%	37.7%		
Secondary school	24.1%	24.4%	26.5%	26.7%	29.0%		
Higher education	5.53%	6.11%	7.58%	7.78%	8.70%		
Number of pregnancies	2.88 (2.16)	2.88 (2.16)	2.96 (2.17)	2.89 (1.94)	2.89 (1.97)	0.999	465
Marital status:						0.126	119
Single	.%	35.3%	31.2%	63.3%	50.0%		
Free union	.%	58.8%	62.5%	36.7%	50.0%		
Married	.%	0.00%	2.08%	0.00%	0.00%		
Divorced	.%	5.88%	4.17%	0.00%	0.00%		
Sex work as main job	0.49 (0.50)	0.48 (0.50)	0.49 (0.50)	0.54 (0.50)	0.59 (0.50)	0.564	675
Work everyday last month	0.92 (0.26)	0.92 (0.27)	0.92 (0.26)	0.95 (0.23)	0.97 (0.17)	0.650	674
Years of experience	3.94 (4.55)	3.89 (4.44)	4.03 (4.50)	4.47 (5.02)	4.61 (5.31)	0.725	669
Works in a brothel:						0.462	675
No	52.5%	53.0%	51.9%	45.1%	42.9%		
Yes	47.5%	47.0%	48.1%	54.9%	57.1%		
Had condomless intercourse (baseline):						0.874	673
No	64.8%	64.4%	66.2%	65.9%	71.4%		

*continued on next page*

Table A2.4 – continued from previous page

	1	2	3	4	5	2*p-value	2* N
Yes	N=200	N=181	N=133	N=91	N=70		
	35.2%	35.6%	33.8%	34.1%	28.6%		
Use of condom (follow up):							
Always	.%	88.2%	97.7%	96.4%	91.3%		0.070
Often	.%	11.8%	2.33%	3.57%	0.00%		
Sometimes	.%	0.00%	0.00%	0.00%	8.70%		
Number of clients (baseline)	4.71 (3.07)	4.80 (3.14)	4.86 (3.16)	4.95 (3.17)	5.08 (3.28)		611
Number of clients (each wave)	4.70 (3.08)	4.06 (4.19)	3.27 (2.74)	2.78 (1.53)	4.35 (3.38)		286
Threshold price (baseline)	1654 (995)	1605 (763)	1602 (769)	1587 (791)	1612 (839)		638
Threshold price (each wave)	1666 (994)	1353 (493)	1435 (501)	1379 (494)	1174 (388)		299
Price of the last intercourse	. (.)	2786 (2455)	2947 (2612)	2231 (1920)	1783 (1242)		101

Note: The table presents the descriptive statistics for time-invariant and time-variant characteristics at each visit, from the first visit to the fifth one. The sample size include only FSWs that were prescribed PrEP at least once. The first five columns represent the number of FSWs that attended the first, second, third, fourth or fifth visit. The p-value is computed from the Pearson test when row-variable is normal and from the Spearman test when it is continuous non normal. If the row-variable is categorical, the p-value for trend is computed from Mantel-Haenszel test of trend. The last column gives the total number of observations available for each variable. Variables are collected at baseline and/or at follow-up. This table can only gives help on intensive margins not extensive one.

Table A2.5: Attrition - Second visit (sample under prescription)

	Missing N=19	Still N=181	2*p-value	2* N
Age	27.7 (6.03)	30.7 (7.04)	0.053	200
Nationality (Ivorian)	0.89 (0.32)	0.56 (0.50)	<0.001	200
Level of education:			0.868	199
Never went to school	42.1%	35.0%		
Primary school	36.8%	34.4%		
Secondary school	21.1%	24.4%		
Higher education	0.00%	6.11%		
Sex work as main job	0.58 (0.51)	0.48 (0.50)	0.430	200
Work everyday last month	0.94 (0.24)	0.92 (0.27)	0.716	199
Years of experience	4.42 (5.59)	3.89 (4.44)	0.692	198
Works in a brothel:			0.819	200
No	47.4%	53.0%		
Yes	52.6%	47.0%		
Had condomless intercourse (baseline):			0.926	199
No	68.4%	64.4%		
Yes	31.6%	35.6%		
Number of clients (baseline)	3.81 (2.17)	4.80 (3.14)	0.111	178
Threshold price (baseline)	1656 (1012)	1605 (763)	0.845	185

Note: The table presents the mean of characteristics and independent t-test between participants (FSW who were prescribed PrEP at least once) who attended a 2nd visit (Still) and those who did not (Missing). The p-value is computed from the Pearson test when row-variable is normal and from the Spearman test when it is continuous non normal. If the row-variable is categorical, the p-value for trend is computed from Mantel-Haenszel test of trend. The last column gives the total number of observations available for each variable. Variables are collected at baseline and/or at follow-up. This table can only give help on intensive margins not extensive one.

Table A2.6: Attrition - Third visit (sample under prescription)

	Missing N=67	Still N=133	2*p-value	2* N
Age	29.1 (6.18)	31.1 (7.30)	0.048	200
Nationality (Ivorian)	0.72 (0.45)	0.53 (0.50)	0.011	200
Level of education:			0.163	199
Never went to school	41.8%	32.6%		
Primary school	37.3%	33.3%		
Secondary school	19.4%	26.5%		
Higher education	1.49%	7.58%		
Sex work as main job	0.49 (0.50)	0.49 (0.50)	0.960	200
Work everyday last month	0.92 (0.27)	0.92 (0.26)	0.989	199
Years of experience	3.76 (4.66)	4.03 (4.50)	0.698	198
Works in a brothel:			0.922	200
No	53.7%	51.9%		
Yes	46.3%	48.1%		
Had condomless intercourse (baseline):			0.686	199
No	62.1%	66.2%		
Yes	37.9%	33.8%		
Number of clients (baseline)	4.41 (2.90)	4.86 (3.16)	0.354	178
Threshold price (baseline)	1625 (821)	1602 (769)	0.853	185

Note: The table presents the mean of characteristics and independent t-test between participants (FSW who were prescribed PrEP at least once) who attended a 3rd visit (Still) and those who did not (Missing). The p-value is computed from the Pearson test when row-variable is normal and from the Spearman test when it is continuous non normal. If the row-variable is categorical, the p-value for trend is computed from Mantel-Haenszel test of trend. The last column gives the total number of observations available for each variable. Variables are collected at baseline and/or at follow-up. This table can only gives help on intensive margins not extensive one.

Table A2.7: Attrition - Fourth visit (sample under prescription)

	Missing N=109	Still N=91	2*p-value	2* N
Age	29.5 (7.10)	31.5 (6.73)	0.036	200
Nationality (Ivorian)	0.68 (0.47)	0.49 (0.50)	0.008	200
Level of education:			0.337	199
Never went to school	40.4%	30.0%		
Primary school	33.9%	35.6%		
Secondary school	22.0%	26.7%		
Higher education	3.67%	7.78%		
Sex work as main job	0.45 (0.50)	0.54 (0.50)	0.212	200
Work everyday last month	0.91 (0.29)	0.95 (0.23)	0.309	199
Years of experience	3.49 (4.08)	4.47 (5.02)	0.135	198
Works in a brothel:			0.074	200
No	58.7%	45.1%		
Yes	41.3%	54.9%		
Had condomless intercourse (baseline):			0.879	199
No	63.9%	65.9%		
Yes	36.1%	34.1%		
Number of clients (baseline)	4.49 (2.98)	4.95 (3.17)	0.323	178
Threshold price (baseline)	1630 (782)	1587 (791)	0.706	185

Note: The table presents the mean of characteristics and independent t-test between participants (FSW who were prescribed PrEP at least once) who attended a 4th visit (Still) and those who did not (Missing). The p-value is computed from the Pearson test when row-variable is normal and from the Spearman test when it is continuous non normal. If the row-variable is categorical, the p-value for trend is computed from Mantel-Haenszel test of trend. The last column gives the total number of observations available for each variable. Variables are collected at baseline and/or at follow-up. This table can only give help on intensive margins not extensive one.

Table A2.8: Attrition - Fifth visit (sample under prescription)

	Missing N=130	Still N=70	2*p-value	2* N
Age	30.1 (6.95)	31.0 (7.09)	0.409	200
Nationality (Ivorian)	0.68 (0.47)	0.43 (0.50)	0.001	200
Level of education:			0.072	199
Never went to school	41.5%	24.6%		
Primary school	33.1%	37.7%		
Secondary school	21.5%	29.0%		
Higher education	3.85%	8.70%		
Sex work as main job	0.44 (0.50)	0.59 (0.50)	0.047	200
Work everyday last month	0.90 (0.30)	0.97 (0.17)	0.031	199
Years of experience	3.57 (4.05)	4.61 (5.31)	0.155	198
Works in a brothel:			0.064	200
No	57.7%	42.9%		
Yes	42.3%	57.1%		
Had condomless intercourse (baseline):			0.200	199
No	61.2%	71.4%		
Yes	38.8%	28.6%		
Number of clients (baseline)	4.50 (2.94)	5.08 (3.28)	0.242	178
Threshold price (baseline)	1608 (754)	1612 (839)	0.975	185

Note: The table presents the mean of characteristics and independent t-test between participants (FSW who were prescribed PrEP at least once) who attended a 5th visit (Still) and those who did not (Missing). The p-value is computed from the Pearson test when row-variable is normal and from the Spearman test when it is continuous non normal. If the row-variable is categorical, the p-value for trend is computed from Mantel-Haenszel test of trend. The last column gives the total number of observations available for each variable. Variables are collected at baseline and/or at follow-up. This table can only gives help on intensive margins not extensive one.

Table A2.9: Summary descriptives table by groups of 'Rank of the visit' (full sample)

	1	2	3	4	5	2*p-value	2* N
	N=330	N=240	N=169	N=115	N=86		
Age	30.7 (7.88)	31.5 (7.94)	32.2 (8.44)	33.0 (8.33)	32.1 (8.27)	0.079	940
Nationality (Ivoirienne)	0.58 (0.49)	0.52 (0.50)	0.51 (0.50)	0.47 (0.50)	0.40 (0.49)	0.024	940
Level of education:							932
Never went to school	34.3%	34.0%	32.1%	30.7%	25.9%		
Coranic school	1.22%	0.84%	0.60%	0.00%	0.00%		
Primary school	33.3%	34.0%	34.5%	35.1%	38.8%		
Secondary school	26.0%	26.5%	26.8%	28.1%	28.2%		
Higher education	5.20%	4.62%	5.95%	6.14%	7.06%		
Number of pregnancies	3.10 (2.21)	3.10 (2.21)	3.13 (2.20)	3.02 (2.06)	3.04 (2.12)	0.994	613
Marital status:							171
Single	.%	28.6%	37.5%	60.5%	51.7%		
Free union	.%	62.9%	51.6%	32.6%	44.8%		
Married	.%	0.00%	1.56%	0.00%	0.00%		
Divorced	.%	2.86%	6.25%	2.33%	3.45%		
Widow	.%	5.71%	3.12%	4.65%	0.00%		
Sex work as main job	0.48 (0.50)	0.48 (0.50)	0.48 (0.50)	0.52 (0.50)	0.56 (0.50)	0.658	940
Work everyday last month	0.92 (0.27)	0.92 (0.27)	0.93 (0.26)	0.95 (0.22)	0.98 (0.15)	0.366	932
Years of experience	3.74 (4.29)	3.89 (4.31)	4.11 (4.41)	4.31 (4.88)	4.49 (5.07)	0.575	927
Works in a brothel:							940
No	49.1%	49.2%	47.3%	38.3%	37.2%		
Yes	50.9%	50.8%	52.7%	61.7%	62.8%		

*continued on next page*

Table A2.9 – continued from previous page

	1	2	3	4	5	2*p-value	2* N
	N=330	N=240	N=169	N=115	N=86		
Had condomless intercourse (baseline):							0.860
No	67.8%	66.9%	69.2%	71.3%	75.6%		938
Yes	31.9%	32.6%	30.8%	28.7%	24.4%		
Don't answer	0.30%	0.42%	0.00%	0.00%	0.00%		
Use of condom (follow up):							0.096
Always	.%	93.8%	98.3%	97.6%	92.9%		159
Often	.%	6.25%	1.72%	2.44%	0.00%		
Sometimes	.%	0.00%	0.00%	0.00%	7.14%		
Number of clients (baseline)	4.59 (3.03)	4.86 (3.17)	5.00 (3.27)	5.23 (3.42)	5.46 (3.64)		844
Number of clients (each wave)	4.51 (2.92)	3.88 (3.76)	3.42 (2.81)	2.72 (1.49)	4.35 (3.38)		371
Threshold price (baseline)	1981 (5761)	2030 (6634)	1589 (786)	1533 (753)	1544 (791)		881
Threshold price (each wave)	1673 (999)	1370 (492)	1440 (501)	1419 (502)	1174 (388)		388
Price of the last intercourse	.	(.)	2478 (2020)	2774 (2545)	1783 (1242)		116

Note: The table represents the descriptive statistics for time-invariant and time-variant characteristics at each visit, from the first visit to the fifth one. The sample size include all FSWs recruited. The first five columns represent the number of FSWs that attended the first, second, third, fourth or fifth visit. The p-value is computed from the Pearson test when row-variable is normal and from the Spearman test when it is continuous non normal. If the row-variable is categorical, the p-value for trend is computed from Mantel-Haenszel test of trend. The last column gives the total number of observations available for each variable. Variables are collected at baseline and/or at follow-up. This table can only gives help on intensive margins not extensive one.

Table A2.10: Attrition - Second visit (sample never under prescription)

	Missing N=71	Still N=59	2*p-value	2* N
Age	29.0 (7.73)	33.8 (9.91)	0.003	130
Nationality (Ivorian)	0.68 (0.47)	0.41 (0.50)	0.002	130
Level of education:			0.202	128
Never went to school	32.9%	31.0%		
Coranic school	2.86%	3.45%		
Primary school	30.0%	32.8%		
Secondary school	25.7%	32.8%		
Higher education	8.57%	0.00%		
Sex work as main job	0.48 (0.50)	0.46 (0.50)	0.811	130
Work everyday last month	0.91 (0.28)	0.91 (0.29)	0.988	126
Years of experience	3.06 (3.75)	3.88 (3.93)	0.239	125
Works in a brothel:			0.232	130
No	49.3%	37.3%		
Yes	50.7%	62.7%		
Had condomless intercourse (baseline):			0.426	130
No	70.4%	74.6%		
Yes	29.6%	23.7%		
Don't answer	0.00%	1.69%		
Number of clients (baseline)	3.81 (2.54)	5.06 (3.29)	0.031	109
Threshold price (baseline)	1750 (1095)	1538 (746)	0.227	113

Note: The table presents the mean of characteristics and independent t-test between non-participants (FSW who were never prescribed PrEP) who attended a 2nd visit (Still) and those who did not (Missing). The p-value is computed from the Pearson test when row-variable is normal and from the Spearman test when it is continuous non normal. If the row-variable is categorical, the p-value for trend is computed from Mantel-Haenszel test of trend. The last column gives the total number of observations available for each variable. Variables are collected at baseline and/or at follow-up. This table can only gives help on intensive margins not extensive one.

Table A2.11: Attrition - Third visit (sample never under prescription)

	Missing N=94	Still N=36	2*p-value	2* N
Age	29.2 (7.44)	36.4 (10.9)	0.001	130
Nationality (Ivorian)	0.61 (0.49)	0.42 (0.50)	0.056	130
Level of education:			0.543	128
Never went to school	32.6%	30.6%		
Coranic school	3.26%	2.78%		
Primary school	28.3%	38.9%		
Secondary school	29.3%	27.8%		
Higher education	6.52%	0.00%		
Sex work as main job	0.48 (0.50)	0.44 (0.50)	0.729	130
Work everyday last month	0.90 (0.30)	0.94 (0.24)	0.413	126
Years of experience	3.04 (3.69)	4.39 (4.09)	0.093	125
Works in a brothel:			0.091	130
No	48.9%	30.6%		
Yes	51.1%	69.4%		
Had condomless intercourse (baseline):			0.475	130
No	69.1%	80.6%		
Yes	29.8%	19.4%		
Don't answer	1.06%	0.00%		
Number of clients (baseline)	3.89 (2.47)	5.50 (3.65)	0.024	109
Threshold price (baseline)	1699 (991)	1543 (852)	0.396	113

Note: The table presents the mean of characteristics and independent t-test between non-participants (FSW who were never prescribed PrEP) who attended a 3rd visit (Still) and those who did not (Missing). The p-value is computed from the Pearson test when row-variable is normal and from the Spearman test when it is continuous non normal. If the row-variable is categorical, the p-value for trend is computed from Mantel-Haenszel test of trend. The last column gives the total number of observations available for each variable. Variables are collected at baseline and/or at follow-up. This table can only gives help on intensive margins not extensive one.

Table A2.12: Attrition - Fourth visit (sample never under prescription)

	Missing N=106	Still N=24	2*p-value	2* N
Age	29.6 (7.67)	38.3 (11.3)	0.001	130
Nationality (Ivorian)	0.59 (0.49)	0.38 (0.49)	0.058	130
Level of education:			0.868	128
Never went to school	31.7%	33.3%		
Coranic school	3.85%	0.00%		
Primary school	30.8%	33.3%		
Secondary school	27.9%	33.3%		
Higher education	5.77%	0.00%		
Sex work as main job	0.47 (0.50)	0.46 (0.51)	0.908	130
Work everyday last month	0.90 (0.30)	0.96 (0.20)	0.275	126
Years of experience	3.37 (3.73)	3.71 (4.35)	0.725	125
Works in a brothel:			0.001	130
No	50.9%	12.5%		
Yes	49.1%	87.5%		
Had condomless intercourse (baseline):			0.041	130
No	67.9%	91.7%		
Yes	31.1%	8.33%		
Don't answer	0.94%	0.00%		
Number of clients (baseline)	3.90 (2.37)	6.26 (4.13)	0.014	109
Threshold price (baseline)	1736 (1014)	1333 (565)	0.013	113

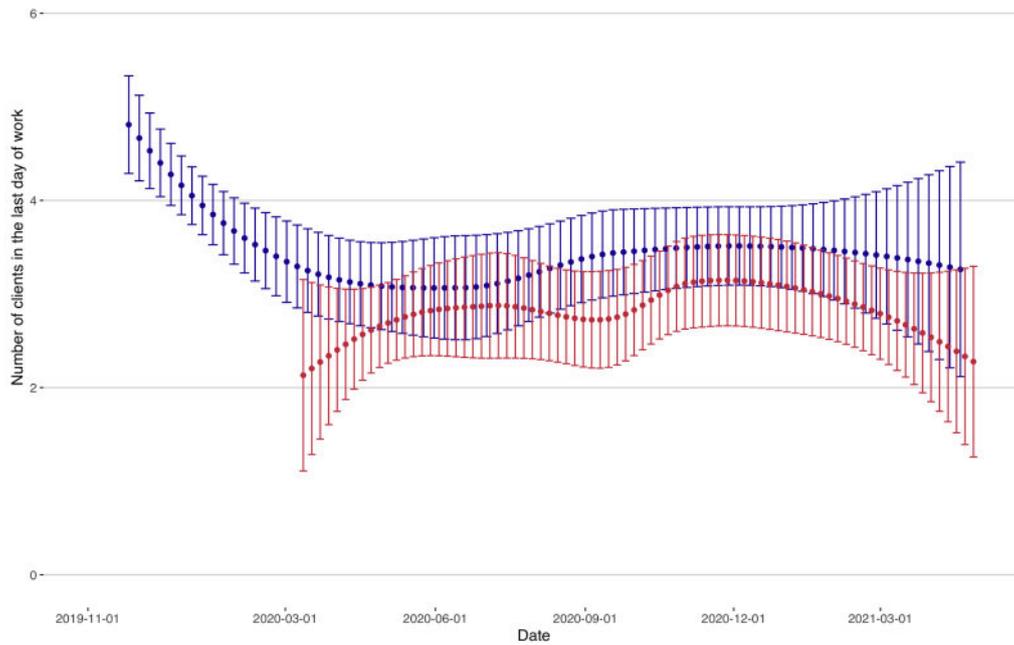
Note: The table presents the mean of characteristics and independent t-test between non-participants (FSW who were never prescribed PrEP) who attended a 4th visit (Still) and those who did not (Missing). The p-value is computed from the Pearson test when row-variable is normal and from the Spearman test when it is continuous non normal. If the row-variable is categorical, the p-value for trend is computed from Mantel-Haenszel test of trend. The last column gives the total number of observations available for each variable. Variables are collected at baseline and/or at follow-up. This table can only gives help on intensive margins not extensive one.

Table A2.13: Attrition - Fifth visit (sample never under prescription)

	Missing N=114	Still N=16	2*p-value	2* N
Age	30.4 (8.50)	36.8 (11.2)	0.042	130
Nationality (Ivorian)	0.60 (0.49)	0.25 (0.45)	0.009	130
Level of education:			0.846	128
Never went to school	32.1%	31.2%		
Coranic school	3.57%	0.00%		
Primary school	29.5%	43.8%		
Secondary school	29.5%	25.0%		
Higher education	5.36%	0.00%		
Sex work as main job	0.47 (0.50)	0.44 (0.51)	0.794	130
Work everyday last month	0.90 (0.30)	1.00 (0.00)	0.001	126
Years of experience	3.36 (3.84)	3.94 (3.96)	0.589	125
Works in a brothel:			0.015	130
No	48.2%	12.5%		
Yes	51.8%	87.5%		
Had condomless intercourse (baseline):			0.153	130
No	69.3%	93.8%		
Yes	29.8%	6.25%		
Don't answer	0.88%	0.00%		
Number of clients (baseline)	3.94 (2.32)	7.06 (4.64)	0.018	109
Threshold price (baseline)	1716 (995)	1250 (447)	0.003	113

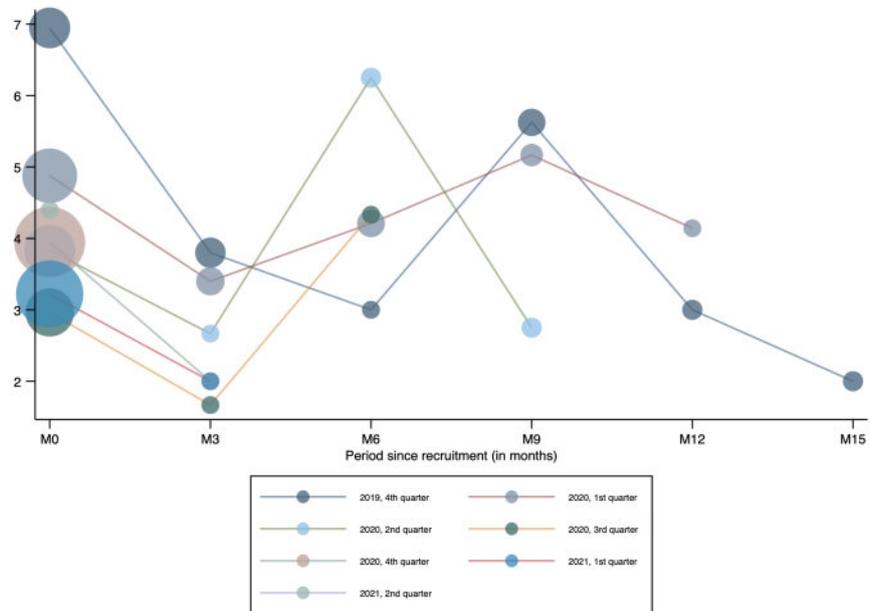
Note: The table presents the mean of characteristics and independent t-test between non-participants (FSW who were never prescribed PrEP) who attended a 5th visit (Still) and those who did not (Missing). The p-value is computed from the Pearson test when row-variable is normal and from the Spearman test when it is continuous non normal. If the row-variable is categorical, the p-value for trend is computed from Mantel-Haenszel test of trend. The last column gives the total number of observations available for each variable. Variables are collected at baseline and/or at follow-up. This table can only gives help on intensive margins not extensive one.

Figure A2.4: Number of clients during the last day of work (baseline and follow-ups)



Note: The graph presents the number of clients during the last day of work. FSWs were asked to give this number at the recruitment and each follow-up. The blue line shows the average number of clients at baseline interview. The red line shows the average number of clients declared in follow-up surveys.

Figure A2.5: Clients trend - seasonality



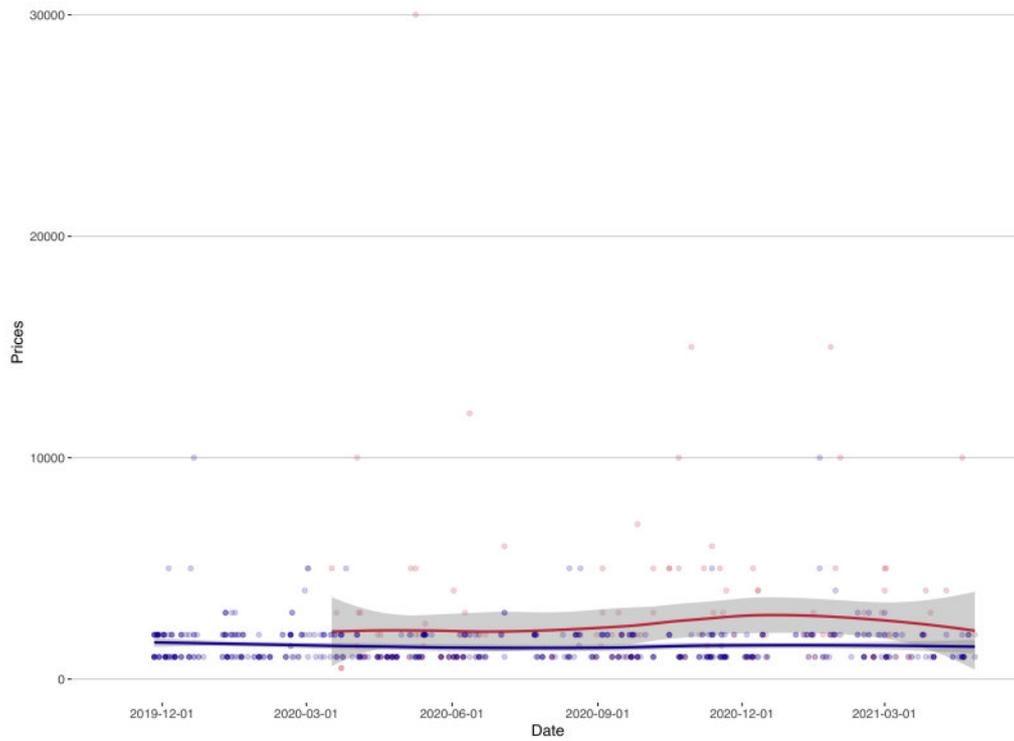
Note: The figure represents the number of clients controlling for the rank of the follow-up survey, from Month 0 (baseline survey) to Month 15 (6th follow-up survey). FSWs are gathered by recruitment period from the 4th quarter 2019 to 2nd quarter 2021. The dots are weighted by the sample size at the time of the survey.

Table A2.14: Prices - Baseline and follow-up surveys

Price's characteristics		n (proportion)
Threshold price (baseline)	1000	128 (49%)
	1500	4 (1.5%)
	2000	106 (41%)
	3000	10 (3.9%)
	4000	2 (0.8%)
	5000	8 (3.1%)
	10000	1 (0.4%)
Threshold price (follow-up)	1000	122 (66%)
	2000	62 (34%)
Threshold price (baseline and follow-up)	<1000 FCFA	250 (56%)
	1001 - 2500 FCFA	172 (39%)
	2501 - 5000 FCFA	20 (4.5%)
	7501 - 10000 FCFA	1 (0.2%)
Price of the last intercourse (follow-up)	<1000 FCFA	73 (45%)
	1001 - 2500 FCFA	52 (32%)
	2501 - 5000 FCFA	28 (17%)
	5001 - 7500 FCFA	3 (1.9%)
	7501 - 10000 FCFA	2 (1.2%)
	>10001 FCFA	4 (2.5%)
How have the prices changed over the past six months ?	Higher than before	4 (2.2%)
	Same as before	126 (68%)
	Smaller than before	54 (29%)
	Don't know	0 (0%)
	Not concerned	1 (0.5%)
	Don't want to answer	1 (0.5%)

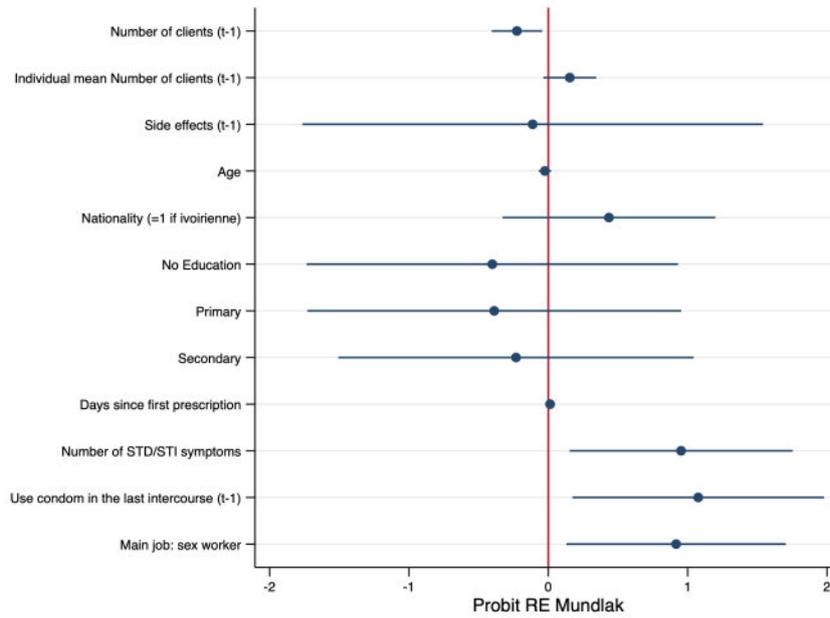
Note: The table describes the distribution of the price of sex using two variables: price floor and price of the last intercourse. The price floor is the one usually charged by FSWs, according to the question's wording. Since prices vary greatly depending on the sexual intercourse, this is the price floor for negotiating the intercourse sex rate. This price is collected at baseline and at each follow-up survey. From the first follow-up, sex workers reported the price of their last sexual encounter, and this price is more subject to variation. Finally, sex workers were asked about their perception of the prices they charged in the follow-up surveys.

Figure A2.6: Sex prices (log transformed)



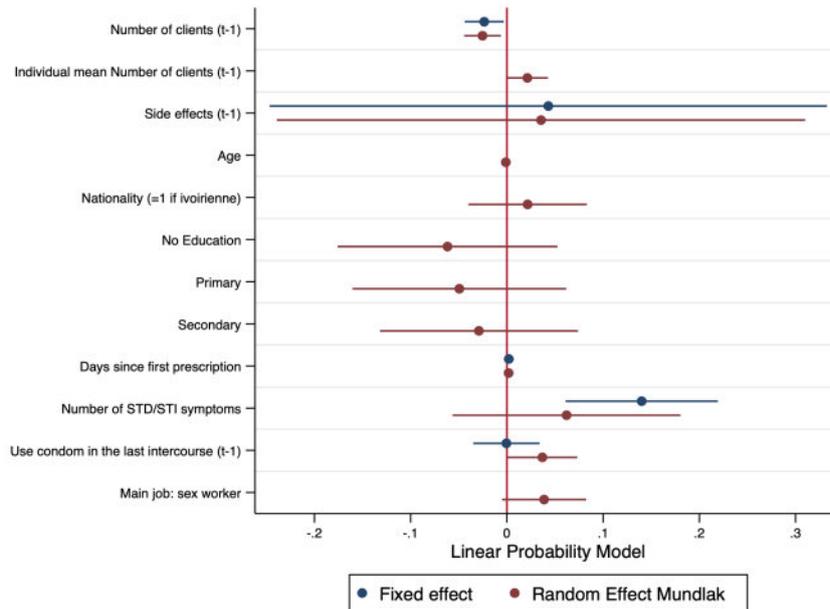
Note: The graph presents the variation of the log transformation of prices. The blue line presents the "usual" price per intercourse, called the price floor. FSWs were asked to give it at baseline and each follow-up. The red line presents the price of the last intercourse. This price was collected during follow-up interviews only.

Figure A2.7: Determinants of treatment adherence - Probit



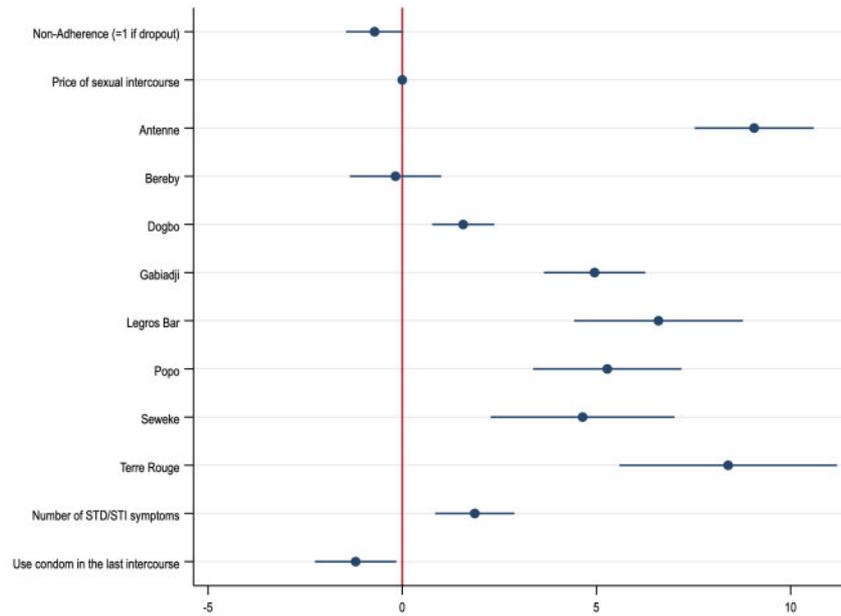
Note: This plot depicts the results of the correlated random effect probit model with Mundlak transformation. Treatment adherence is regressed on the following variables: the number of clients, the side effects of the treatment, the age, the nationality, the level of education, the number of days since the first prescription, the number of STD/STI symptoms, the use of condoms, being a sex worker as the main job.

Figure A2.8: Determinants of treatment adherence - Linear Probability Model



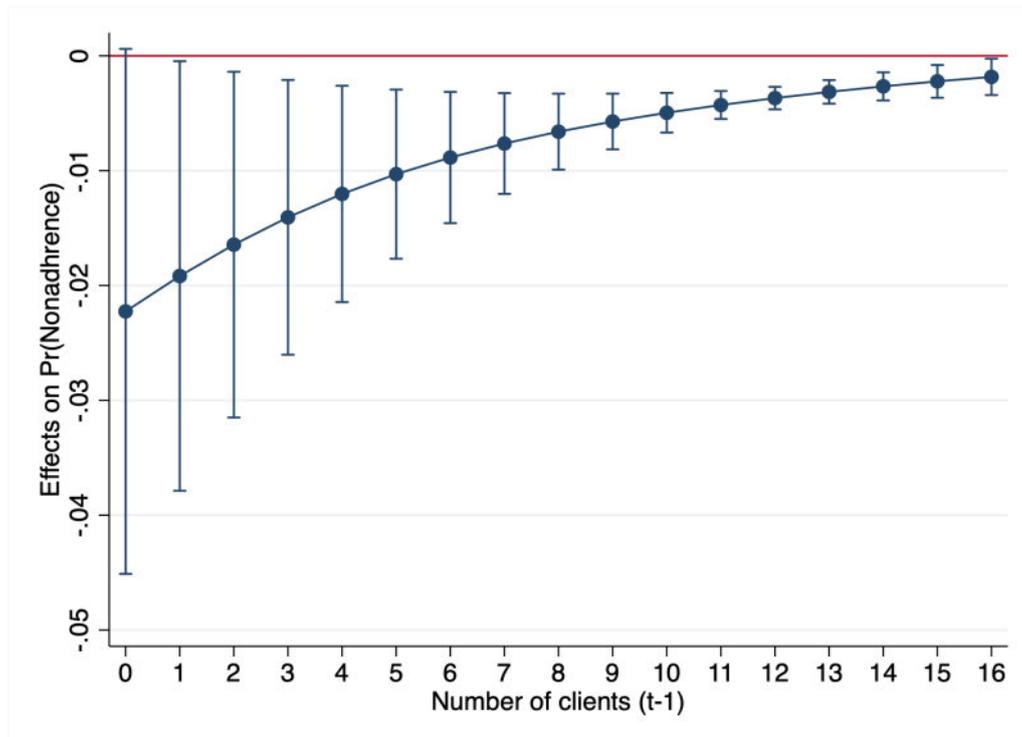
Note: This plot depicts the coefficient of the fixed effect linear probability model and the random effect linear probability model with Mundlak procedure. Treatment adherence is regressed on the following variables: the number of clients, the side effects of the treatment, the age, the nationality, the level of education, the number of days since the first prescription, the number of STD/STI symptoms, the use of condoms, being a sex worker as the main job.

Figure A2.9: Determinants of the Number of clients



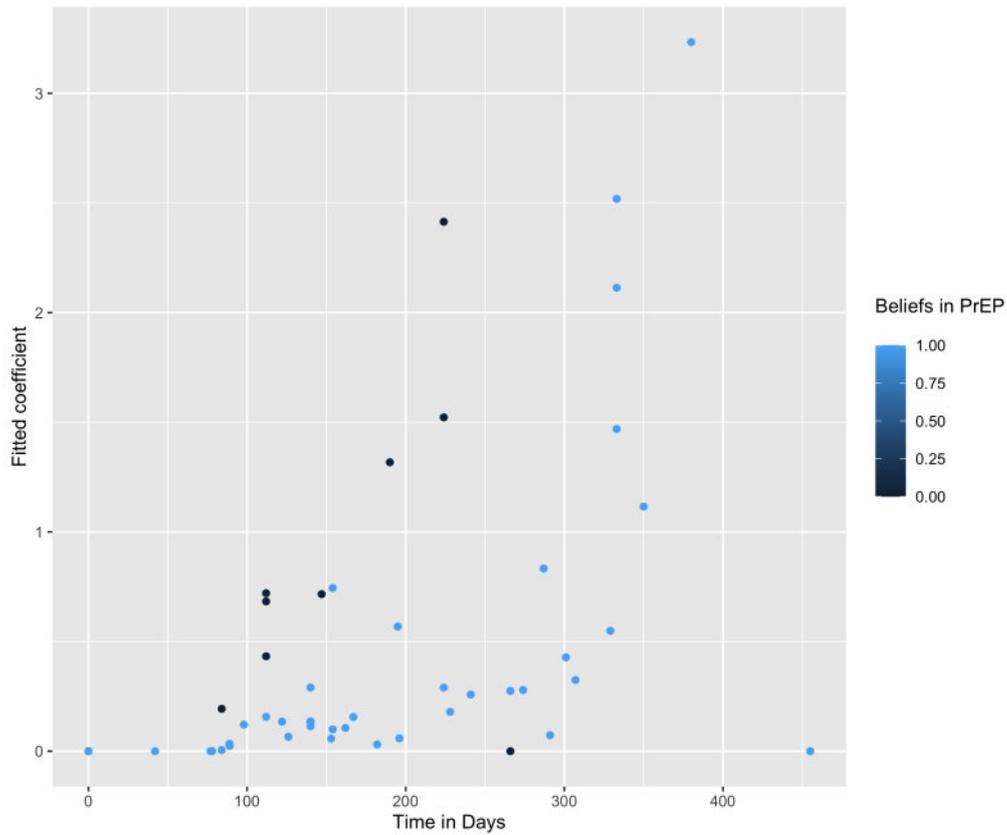
Note: This plot depicts the coefficients of the fixed effect OLS for the number of clients. The number of clients is regressed on the following variables: adherence, price floor of sexual intercourse, sex work sites, number of STD/STI symptoms, use of condoms in the last intercourse.

Figure A2.10: Marginal impact of the number of clients



Note: This graph represents the marginal variation in the probability to drop the treatment per additional clients after the simultaneous equations model. The dependent variable is non-adherence, which equals 0 if the FSW is on PrEP and 1 if she is off PrEP. The graph shows that the probability of discontinuing the drug decreases by 1 percent with each additional client.

Figure A2.11: Survival analysis by beliefs



Note: This graph represents the fitted coefficient of the survival analysis using Cox regression model augmented with the binary variable for belief in PrEP efficacy. The Cox regression model is a semi-parametric model to fit regression for survival analysis. The dependent variable is the number of days between the events of “non-adherence”, which equals 0 if the FSW is on PrEP and 1 if she is off PrEP. The independent variables are the number of clients, the side effects of the treatment, the age, the nationality, the level of education, the number of days since the first prescription, the number of STD/STI symptoms, the use of condoms, being a sex worker as the main job. The fitted coefficient represents the hazard ratio of the occurrence of the event according to the group of belief in PrEP efficacy. The latter equals 1 if the FSW believes in PrEP efficacy and 0 if not. “The hazard ratio is interpreted as the instantaneous rate of occurrence of the event of interest in those who are still at risk for the event. It is not a risk, though it is commonly interpreted as such.” Rich et al.(2010).

Table A2.15: SEM - Compliance 5,5 days a week

	Simultaneous equations	
	Coeff.	SE
<b>Non-adherence (=1 if dropout)</b>		
Number of clients (t-1)	-0.228***	(0.0236)
Individual mean Number of clients	0.231***	(0.0393)
Age	-0.0191	(0.0157)
Nationality (=1 if ivoirienne)	0.358	(0.259)
NA	0	(.)
Niveau primaire	-0.177	(0.222)
Niveau secondaire	-0.349	(0.252)
Niveau supérieur	0.256	(0.216)
Health (=1 if HIV negative) (t-1)	0	(.)
Side effects (t-1)	-0.711	(0.686)
Number of STD/STI symptoms (t-1)	0.0479	(0.254)
Use condom in the last intercourse (t-1)	0	(.)
Main job: sex worker	0.483***	(0.165)
Days since first prescription	0.00956***	(0.000323)
Constant	-1.123	(0.785)
<b>Number of clients</b>		
Non-adherence (=1 if dropout)	-2.452***	(0.0343)
Price of sexual intercourse	0.00120	(.)
Adjamene	0	(.)
Antenne	5.283	(.)
Bereby	-2.967***	(0.716)
Dogbo	4.345***	(1.063)
Gabiadji	3.764***	(1.068)
Legros Bar	-1.365	(.)
Moussadougou	0.721	(0.759)
Popo	-0.277	(.)
Seweke	-6.777***	(1.053)
Terre Rouge	-3.629***	(1.013)
Wate	2.470***	(0.918)
Number of STD/STI symptoms	-0.549	(0.653)
Use condom in the last intercourse	4.119	(.)
Days since first prescription	0.0161	(.)
Constant	-5.156	(.)
$\gamma_{2,1}$	-2.452***	(0.0343)
$\ln \sigma_2$	1.153***	(0.0000171)
$\operatorname{atanh} \rho_{1,2}$	12.38	(.)
Observations	390	

Note: \*\*\* p <.01, \*\*p <.05, \* p <.1 Standard errors are in parenthesis. The table presents the result of a SEM for robustness test. Individual compliance is set at 5.5 days a week. The simultaneous equations model includes a non-linear and a linear equations. The non-linear equation is a probit with Mundlak specification. The main outcome is *Non-adherence* and the Mundlak specification is for the independent variable of interest. It includes the mean for the number of clients at individual level. The linear equation is a fixed effect OLS of the *Number of clients*. It includes fixed effect at individual level. Both equations include a set of covariates described in section 4.3. In the bottom part of the table,  $\sigma$  and  $\rho$  represents  $\eta$ . Specifically,  $\sigma$  is the standard deviation parameter for the error and  $\rho$  is the correlation coefficient for each pair. The parameters are unbounded with logarithm and arc-hyperbolic tangent transformations, respectively.

Table A2.16: SEM - Cluster at sex work sites

	Simultaneous equations	
	Coeff.	SE
<b>Non-adherence (=1 if dropout)</b>		
Number of clients (t-1)	-0.161***	(0.0529)
Individual mean Number of clients	0.121**	(0.0585)
Age	-0.0223	(0.0199)
Nationality (=1 if ivoirienne)	0.296	(0.296)
NA	0	(.)
Niveau primaire	-0.0992	(0.294)
Niveau secondaire	0.0392	(0.352)
Niveau supérieur	0.202	(0.441)
Side effects (t-1)	0.0211	(0.527)
Number of STD/STI symptoms (t-1)	0	(.)
Use condom in the last intercourse (t-1)	0.531	(0.369)
Main job: sex worker	0.511*	(0.278)
Days since first prescription	0.00852***	(0.00111)
Constant	-1.791**	(0.851)
<b>Number of clients</b>		
Non-adherence (=1 if dropout)	-1.980	(1.391)
Price of sexual intercourse	0.000729	(0.000669)
Adjamene	0	(.)
Antenne	8.028***	(2.721)
Bereby	-2.450*	(1.324)
Dogbo	3.295***	(0.914)
Gabiadji	2.654*	(1.592)
Legros Bar	-1.930	(2.331)
Moussadougou	-0.310	(1.262)
Popo	2.828	(2.836)
Seweke	-6.234*	(3.205)
Terre Rouge	-4.097**	(1.604)
Wate	-0.281	(1.003)
Number of STD/STI symptoms	0.135	(1.267)
Use condom in the last intercourse	1.152	(1.330)
Days since first prescription	0.0122	(0.0149)
Constant	-2.031	(2.021)
$\ln \sigma_2$	0.759	(0.625)
$\operatorname{atanh} \rho_{12}$	2.182***	(0.698)
Observations	401	

Note: \*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .1$  Standard errors are in parenthesis. Outcomes are clustered at sex work sites level to control for within-site correlation. The simultaneous equations model includes a non-linear and a linear equations. The non-linear equation is a probit with Mundlak specification. The main outcome is *Non-adherence* and the Mundlak specification is for the independent variable of interest. It includes the mean for the number of clients at individual level. The linear equation is a fixed effect OLS of the *Number of clients*. It includes fixed effect at individual level. Both equations include a set of covariates described in section 4.3. In the bottom part of the table,  $\sigma$  and  $\rho$  represents  $\eta$ . Specifically,  $\sigma$  is the standard deviation parameter for the error and  $\rho$  is the correlation coefficient for each pair. The parameters are unbounded with logarithm and arc-hyperbolic tangent transformations, respectively.

Table A2.17: SEM - Sample restricted

	Simultaneous equations	
	Coeff.	SE
<b>Non-adherence (=1 if dropout)</b>		
Number of clients (t-1)	-0.152***	(0.0536)
Individual mean Number of clients	0.115*	(0.0674)
Age	-0.0245	(0.0182)
Nationality (=1 if ivoirienne)	0.377	(0.325)
NA	0	(.)
Niveau primaire	-0.105	(0.271)
Niveau secondaire	0.0360	(0.382)
Niveau supérieur	0.136	(0.543)
Use condom in the last intercourse (t-1)	0.550**	(0.253)
Side effects (t-1)	-0.0371	(0.674)
Number of STD/STI symptoms (t-1)	0	(.)
Main job: sex worker	0.579**	(0.271)
Days since first prescription	0.00818***	(0.000954)
Constant	-1.670**	(0.851)
<b>Number of clients</b>		
Non-adherence (=1 if dropout)	-2.113**	(0.898)
Price of sexual intercourse	0.000892***	(0.000165)
Adjamene	0	(.)
Antenne	8.539***	(1.692)
Bereby	-2.809***	(0.865)
Dogbo	4.257***	(0.993)
Gabiadji	1.718	(1.570)
Legros Bar	-3.324*	(1.935)
Moussadougou	-1.852	(1.451)
Popo	3.107**	(1.542)
Seweke	-8.014***	(2.226)
Terre Rouge	-5.703***	(1.409)
Wate	-1.349	(1.453)
Number of STD/STI symptoms	-0.202	(0.508)
Use condom in the last intercourse	2.254***	(0.750)
Days since first prescription	0.0122	(0.00834)
Constant	-2.250	(1.718)
$\ln \sigma_2$	0.880**	(0.366)
$\operatorname{atanh} \rho_{12}$	2.220***	(0.403)
Observations	313	

Note: The table presents the result of a SEM for robustness test. The sample is restricted to individuals with at least 3 different observations in time. The simultaneous equations model includes a non-linear and a linear equations. The non-linear equation is a probit with Mundlak specification. The main outcome is *Non-adherence* and the Mundlak specification is for the independent variable of interest. It includes the mean for the number of clients at individual level. The linear equation is a fixed effect OLS of the *Number of clients*. It includes fixed effect at individual level. Both equations include a set of covariates described in section 4.3. In the bottom part of the table,  $\sigma$  and  $\rho$  represents  $\eta$ . Specifically,  $\sigma$  is the standard deviation parameter for the error and  $\rho$  is the correlation coefficient for each pair. The parameters are unbounded with logarithm and arc-hyperbolic tangent transformations, respectively.

Table A2.18: SEM - Mundlak specification at sex work site level

	Simultaneous equations	
	Coeff.	SE
<b>Non-adherence (=1 if dropout)</b>		
Number of clients (t-1)	-0.0125***	(0.00216)
Monthly sex work site mean Number of clients	0.0202***	(0.00363)
Age	-0.0139	(0.0160)
Nationality (=1 if ivoirienne)	0.285	(0.294)
Education: None	0	(.)
Primary	-0.103	(0.250)
Secondary	0.104	(0.344)
Higher	0.335	(0.473)
Side effects (t-1)	0.268	(0.688)
Number of STD/STI symptoms (t-1)	0	(.)
Use condom in the last intercourse (t-1)	0.0168**	(0.00714)
Main job: sex worker	0.530**	(0.246)
Days since first prescription	0.00894***	(0.000873)
Constant	-1.868***	(0.677)
<b>Number of clients</b>		
Adherence (=1 if dropout)	-39.32***	(2.005)
Price of sexual intercourse	0.000839***	(0.000125)
Sex work site: AD	0	(.)
AN	15.20***	(1.871)
BE	-4.430***	(0.759)
DO	-0.607	(0.994)
GAi	2.389	(18.62)
LB	-28.07	(24.45)
MO	-9.692	(13.24)
PO	9.175***	(1.686)
SE	-33.27	(24.46)
TR	-8.311	(22.39)
WA	7.628	(16.75)
Number of STD/STI symptoms	0.0399	(0.390)
Use condom in the last intercourse	0.986*	(0.506)
Constant	9.552	(27.98)
ln _2	-0.808	(0.844)
atanh $\rho_{12}$	0.189	(4.470)
Observations	401	

Note: The table presents the result of a SEM for robustness test. It includes the mean for the number of clients at the sex work site level instead of individual level. The simultaneous equations model includes a non-linear and a linear equations. The non-linear equation is a probit with Mundlak specification. The main outcome is *Non-adherence* and the Mundlak specification is for the independent variable of interest. The linear equation is a fixed effect OLS of the *Number of clients*. It includes fixed effect at individual level. Both equations include a set of covariates described in section 4.3. In the bottom part of the table,  $\sigma$  and  $\rho$  represents  $\eta$ . Specifically,  $\sigma$  is the standard deviation parameter for the error and  $\rho$  is the correlation coefficient for each pair. The parameters are unbounded with logarithm and arc-hyperbolic tangent transformations, respectively.

Table A2.19: SEM - Marital status as covariate

	Simultaneous equations	
	(1)	
<b>Non-adherence (=1 if dropout)</b>		
Number of clients (t-1)	-0.170**	(0.0688)
Individual mean Number of clients (t-1)	0.104	(0.0750)
Age	-0.0212	(0.0184)
Nationality (=1 if ivoirienne)	0.501	(0.334)
NA	0	(.)
Niveau primaire	-0.203	(0.266)
Niveau secondaire	0.138	(0.395)
Niveau supérieur	0.0884	(0.552)
Side effects (t-1)	0.373	(0.731)
Number of STD/STI symptoms (t-1)	0	(.)
Use condom in the last intercourse (t-1)	0.583*	(0.337)
Main job: sex worker	0.574**	(0.266)
Days since first prescription	0.00767***	(0.000960)
Married	0.691	(0.421)
Constant	-2.370**	(0.961)
<b>Number of clients</b>		
Adherence (=1 if dropout)	-0.897**	(0.351)
Price of sexual intercourse	0.000263	(0.000273)
Adjamene	0	(.)
Antenne	9.333***	(1.573)
Bereby	-0.219	(1.090)
Dogbo	1.655	(1.274)
Gabiadji	4.947***	(1.564)
Legros Bar	6.423***	(1.535)
Moussadougou	6.774***	(2.290)
Popo	5.155***	(1.429)
Seweke	4.657**	(2.376)
Terre Rouge	8.270***	(1.423)
Wate	2.659	(2.290)
Number of STD/STI symptoms	1.477***	(0.508)
Use condom in the last intercourse	-1.166***	(0.425)
Days since first prescription	0.000225	(0.00106)
Constant	-1.869	(1.744)
<b>lnsig_2</b>		
Constant	0.412***	(0.0409)
<b>atanhrho_12</b>		
Constant	0.516	(0.357)
Observations	517	

Note: The table presents the result of a SEM for robustness test. It includes the marital status as a covariate. The simultaneous equations model includes a non-linear and a linear equations. The non-linear equation is a probit with Mundlak specification. The main outcome is *Non-adherence* and the Mundlak specification is for the independent variable of interest. The linear equation is a fixed effect OLS of the *Number of clients*. It includes fixed effect at individual level. Both equations include a set of covariates described in section 4.3. In the bottom part of the table,  $\sigma$  and  $\rho$  represents  $\eta$ . Specifically,  $\sigma$  is the standard deviation parameter for the error and  $\rho$  is the correlation coefficient for each pair. The parameters are unbounded with logarithm and arc-hyperbolic tangent transformations, respectively.

Table A2.20: SEM - Adherence = 1

	Simultaneous equations	
	(1)	
<b>Adherence (=1 if adhere)</b>		
Number of clients (t-1)	0.175***	(0.0674)
Individual mean Number of clients	-0.106	(0.0741)
Age	0.0244	(0.0184)
Nationality (=1 if ivoirienne)	-0.547	(0.337)
NA	0	(.)
Niveau primaire	0.245	(0.271)
Niveau secondaire	-0.0660	(0.398)
Niveau supérieur	-0.0364	(0.526)
Side effects (t-1)	-0.304	(0.732)
Number of STD/STI symptoms (t-1)	0	(.)
Use condom in the last intercourse (t-1)	-0.483	(0.347)
Individual mean Number of condoms	-0.868	(1.290)
Main job: sex worker	-0.589**	(0.265)
Days since first prescription	-0.00772***	(0.000948)
married=0	0	(.)
married=1	-0.520	(0.448)
Constant	2.567**	(1.186)
<b>Number of clients</b>		
Adherence	1.204***	(0.368)
Price of sexual intercourse	0.000284	(0.000301)
Adjamene	0	(.)
Antenne	9.809***	(1.666)
Bereby	-0.479	(1.178)
Dogbo	1.660	(1.347)
Gabiadji	5.026***	(1.682)
Legros Bar	6.184***	(1.656)
Moussadouougou	6.335**	(2.478)
Popo	5.458***	(1.528)
Seweke	4.276*	(2.517)
Terre Rouge	8.343***	(1.534)
Wate	2.947	(2.461)
Number of STD/STI symptoms	1.045**	(0.515)
Use condom in the last intercourse	-0.428	(0.428)
Days since first prescription	0.0000103	(0.00110)
Constant	-3.395*	(1.876)
Insig_2	0.490***	(0.0409)
atanhrho_12	-0.874**	(0.442)
Observations	533	

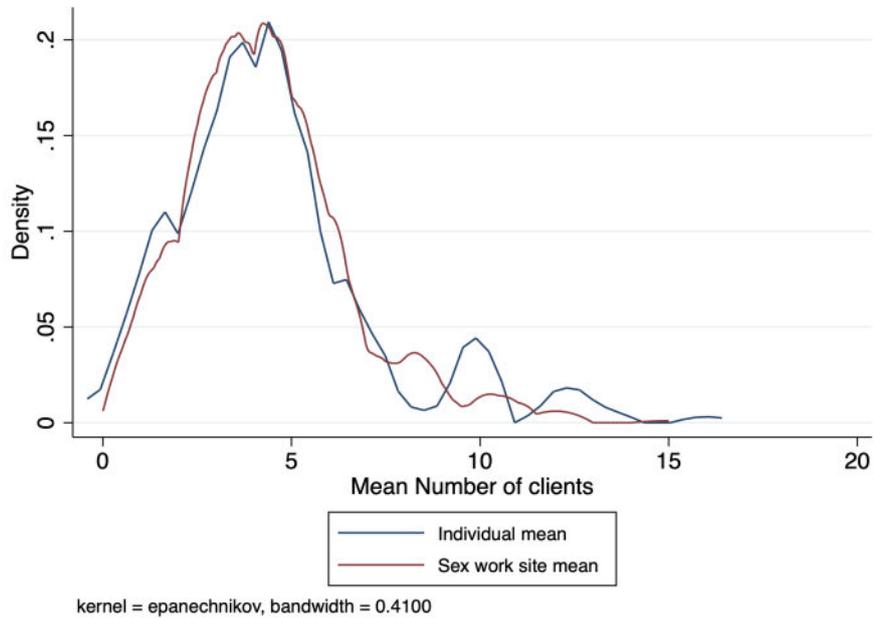
Note: \*\*\* p < .01, \*\*p < .05, \* p < .1 Standard errors (SE) are in brackets. The table presents the result of a simultaneous non-linear equation model. The simultaneous equations model includes a non-linear and a linear equations. The non-linear equation is a probit with Mundlak specification. The main outcome is *Adherence* and the Mundlak specification is for the independent variable of interest, i.e. the individual mean for the number of clients. The linear equation is a fixed effect OLS of the *Number of clients*. It includes fixed effect at individual level. The simultaneous equations model cannot include random effect in the non-linear regression because of the individual fixed effect in the linear regression. Random effects are assumed to be uncorrelated with the other regressors, normally distributed across groups, and not individually identified. Fixed effects are individually identified and can be correlated with the other variables. In the bottom part of the table,  $\sigma$  and  $\rho$  represent  $\eta$ . Specifically,  $\sigma$  is the standard deviation parameter for the error and  $\rho$  is the correlation coefficient for each pair. The parameters are unbounded with logarithm and arc-hyperbolic tangent transformations, respectively.

Table A2.21: SEM - Mundlak specification for the use of condom

	Simultaneous equations	
	(1)	
<b>Non-adherence (=1 if dropout)</b>		
Number of clients (t-1)	-0.168**	(0.0685)
Individual mean Number of clients	0.105	(0.0750)
Age	-0.0214	(0.0185)
Nationality (=1 if ivoirienne)	0.525	(0.336)
NA	0	(.)
Niveau primaire	-0.230	(0.270)
Niveau secondaire	0.115	(0.397)
Niveau supérieur	0.0826	(0.551)
Side effects (t-1)	0.333	(0.733)
Number of STD/STI symptoms (t-1)	0	(.)
Use condom in the last intercourse (t-1)	0.516	(0.350)
Individual mean Number of condoms	0.804	(1.247)
Main job: sex worker	0.569**	(0.268)
Days since first prescription	0.00763***	(0.000971)
Married	0.605	(0.437)
Constant	-2.759**	(1.167)
<b>Number of clients</b>		
Adherence (=1 if dropout)	-0.893**	(0.349)
Price of sexual intercourse	0.000264	(0.000273)
Adjamene	0	(.)
Antenne	9.331***	(1.572)
Bereby	-0.226	(1.090)
Dogbo	1.657	(1.274)
Gabiadji	4.939***	(1.564)
Legros Bar	6.414***	(1.535)
Moussadougou	6.762***	(2.293)
Popo	5.151***	(1.429)
Seweke	4.643*	(2.377)
Terre Rouge	8.266***	(1.423)
Wate	2.643	(2.292)
Number of STD/STI symptoms	1.482***	(0.505)
Use condom in the last intercourse	-1.167***	(0.425)
Days since first prescription	0.000210	(0.00106)
Constant	-1.858	(1.745)
lnsig_2	0.413***	(0.0410)
atanhrho_12	0.525	(0.360)
Observations	517	

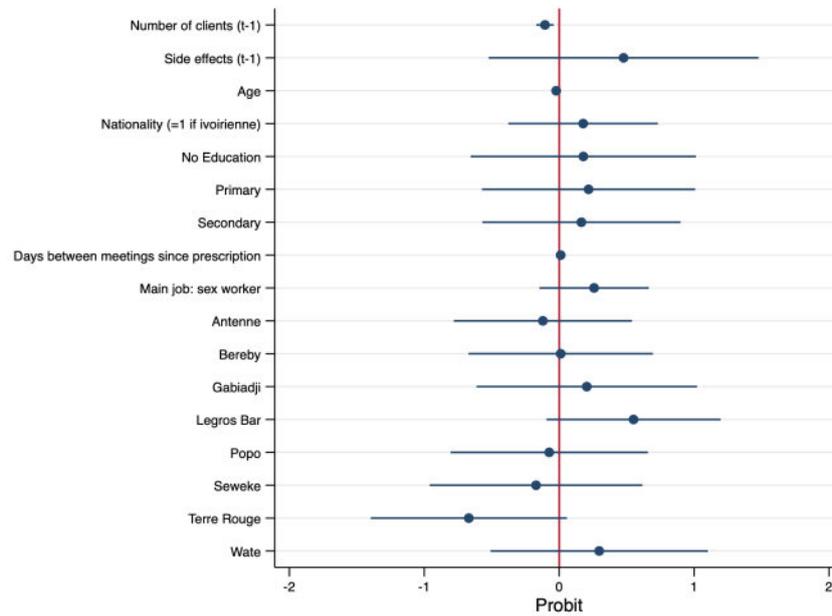
Note: The table presents the result of a SEM for robustness test. It includes the mean for using a condom in the last sex intercourse. The simultaneous equations model includes a non-linear and a linear equations. The non-linear equation is a probit with Mundlak specification. The main outcome is *Non-adherence* and the Mundlak specification is for the independent variable of interest. The linear equation is a fixed effect OLS of the *Number of clients*. It includes fixed effect at individual level. Both equations include a set of covariates described in section 4.3. In the bottom part of the table,  $\sigma$  and  $\rho$  represents  $\eta$ . Specifically,  $\sigma$  is the standard deviation parameter for the error and  $\rho$  is the correlation coefficient for each pair. The parameters are unbounded with logarithm and arc-hyperbolic tangent transformations, respectively.

Figure A2.12: Kernel density - Mean at individual and sex work site levels



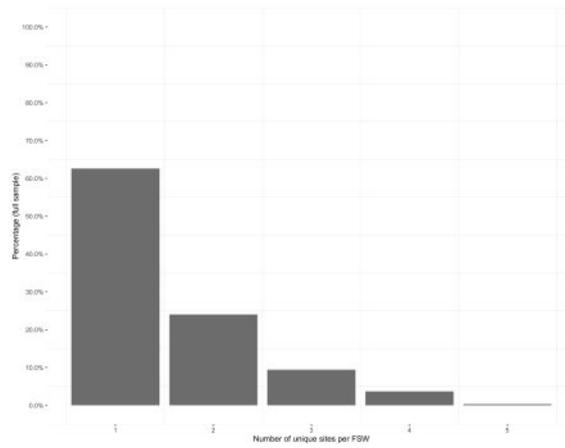
Note: The figure shows the probability density function of the average of the number of clients at individual and sex work sites level. The two groups are compared to assess which one variate the most to better fit the Mundlak procedure. The function at sex work sites level show less variation at the end of the distribution than at individual level.

Figure A2.13: Condition of exclusion restriction - Probit regression with sex work sites



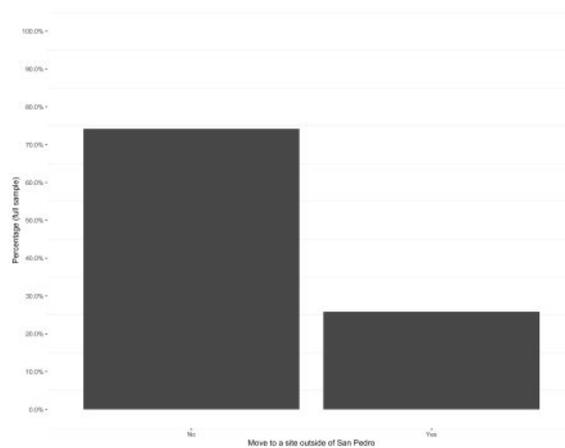
Note: The figure plots coefficients of a probit regression to test the validity of the exclusion restriction in eq. 2.8 without neither Mundlak procedure nor random effects. The dependent variable is the *adherence*. Treatment adherence is regressed on the following variables: the number of clients, the side effects of the treatment, the age, the nationality, the level of education, the number of days since the first prescription, the number of STD/STI symptoms, the use of condoms, being a sex worker as the main job. This robustness test includes sex work sites. The coefficient of sex work sites is not significant and discards the violation of exclusion restriction.

Figure A2.14: FSWs' mobility



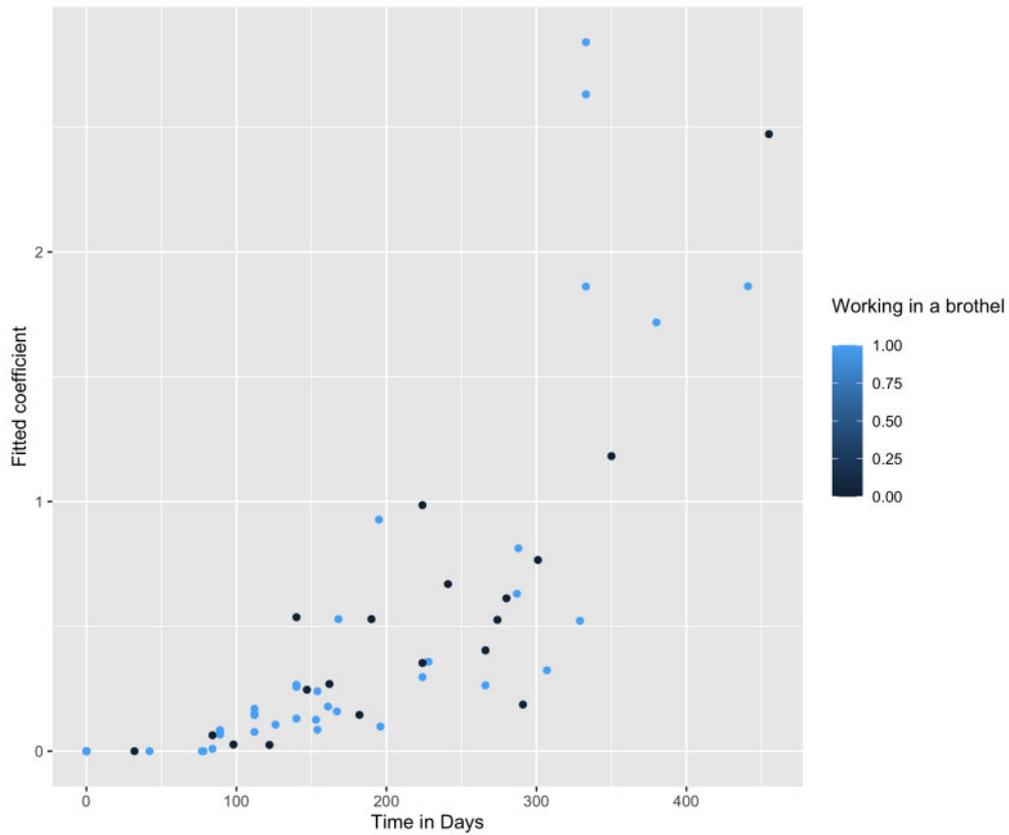
Note: The graph represents the number of unique sex work sites visited per FSW. It is based on the baseline survey and the mobility report in the follow-up surveys. The sample includes every FSWs who had at least one visit in the medical truck.

Figure A2.15: Mobility outside San Pedro



Note: The graph represents the proportion of FSWs who moved at least once outside San Pedro. The sample includes every FSWs who had at least one visit in the medical truck.

Figure A2.16: Survival analysis by brothel



Note: This graph represents the fitted coefficient of the survival analysis using Cox regression model augmented with the binary variable for belief in PrEP efficacy. The Cox regression model is a semi-parametric model to fit regression for survival analysis. The dependent variable is the number of days between the events of “non-adherence”, which equals 0 if the FSW is on PrEP and 1 if she is off PrEP. The independent variables are the number of clients, the side effects of the treatment, the age, the nationality, the level of education, the number of days since the first prescription, the number of STD/STI symptoms, the use of condoms, being a sex worker as the main job. The fitted coefficient represents the hazard ratio of the occurrence of the event according to the group “Working in brothel”. The latter equals 1 if the FSW works in a brothel and 0 if not. “The hazard ratio is interpreted as the instantaneous rate of occurrence of the event of interest in those who are still at risk for the event. It is not a risk, though it is commonly interpreted as such.” Rich et al.(2010).



## Chapter 3

# Children's health and taxing sugar-sweetened beverages in Mexico

### Abstract

Fifty-four countries have adopted the “sin tax” on sugar-sweetened beverages (SSBs) to reverse sugar consumption's impact on chronic diseases. On January 1st, 2014, Mexico implemented a Special Tax on Production and Services (*Impuesto Especial de Productos y Servicios –IEPS*), introducing an excise of one peso per liter on SSBs. Could the price increase following the implementation of the SSBs' tax, have created an in-utero shock that would result in a diminution of children's obesity? Two methods are used with the household and price databases from the Instituto Nacional de Estadística y Geografía. The first strategy takes advantage of the geographical variation in prices to compare children born before and after the implementation of the tax. The second strategy controls for unobservable characteristics with mother-fixed effects. The findings indicate a decrease in height but no conclusive impacts on weight, body mass index, overweight, or obesity.

**Keywords:** sugar-sweetened beverages, sin tax, obesity, scarcity.

**JEL Codes:** I12, I18, D12, H20.

## 1 Introduction

Obesity is becoming a disease burden in several low and middle-income countries (LMICs) like Egypt, Mexico, and South Africa ([Ritchie and Roser 2020](#)). Sugar consumption is one of the main nutritional behaviors accelerating obesity epidemics and other chronic diseases such as cardiovascular disease. In Mexico, where the obesity rate reaches 30% of the general population, sugar-sweetened beverages (SSBs) represented 70% of additive sugars in 2012, which hit 12.5% of the total energy intake, and is often associated with the obesity epidemic ([Sánchez-Romero et al. 2020](#)). Fifty-four countries have adopted the “sin tax” on SSBs to reverse sugar consumption. On January 1st, 2014, Mexico implemented a Special Tax on Production and Services (*Impuesto Especial de Productos y Servicios –IEPS*), introducing one excise peso per liter on SSBs, corresponding to SSBs’ prices rising by 10% on average.

Although SSBs are the largest sources of sugar intake, fighting obesity is a multi-dimensional challenge as it also includes various behavioral changes like a nutritional diet and physical activity ([Cawley 2015](#)). Recent studies show that nutrition and lifestyle during the pre-conception period have a long-term impact on a future child’s health ([Stephenson et al. 2018](#)) and could increase the likelihood of obesity ([Heslehurst et al. 2019](#), [Godfrey et al. 2017](#), [Poston et al. 2016](#)).

This study focuses on the in-utero effects of the SSBs tax on children’s health outcomes, such as weight, height, body mass index (BMI), overweight, and obesity. The case of Mexico is particularly interesting because it is one of the countries most affected by childhood obesity worldwide ([Ritchie and Roser 2020](#)). Mexico is also the only country, to our knowledge, with a large and deep enough database to study the evolution of health outcomes since the implementation of the tax. By studying the effect of this tax, we assess if a public policy can stimulate a change in mothers’ nutritional behavior that would impact the children’s health outcomes.

The tax has reduced SSBs purchases by an average of 6% (12 ml/capita/day) ([Sánchez-Romero et al. 2020](#), [Colchero et al. 2016](#)). Predictions have estimated the impact of the tax between -2/-3kg ([Grogger 2017](#)) and -1kg ([Andalon and Gibson](#)

2017), but people would substitute sugar-drink calories with other ones (Aguilar et al. 2021). The tax had negative spillovers on diarrhea prevalence (Gutierrez and Rubli 2021) in areas where SSBs could not be substituted for clean water. Actually, SSBs prices increased with some heterogeneity between regions (Grogger 2017, Gračner et al. 2022). To our knowledge, either pregnant women were excluded from the sample Gutierrez and Rubli (2021), or they were not studied, as highlighted by Aguilar et al. (2021).

This paper uses the Mexican Health and Nutrition Survey data set, published in 2012, 2016, 2018, and 2020 by the *Instituto Nacional de Estadística y Geografía* (INEGI), which provides information on women and children's health and nutrition. Thanks to this database, I can connect 8,494 children to their 4,627 mothers within the surveyed households, even if the sample will be reduced after controlling for individual characteristics. This database provides information on height and weight needed to calculate the BMI and the likelihood of being overweight or obese. Sugar consumption can also disrupt the cognitive development of children (Cohen et al. 2018). The discussion section includes a child's cognitive development outcome based on the 2018 database. SSBs price variation is measured with the data set published by INEGI. It gathers the prices of consumption goods collected from retailers around the country. This data set will measure price variations before and after the implementation of the tax and between States.

Two identification strategies are used to assess the average and heterogeneous impact of the tax on children's health outcomes. The first strategy, similar to Gračner et al. (2022), takes advantage of the time and geographic variation to compute a difference-in-differences and gives the Average Treatment Effect of the tax. As the results were inconclusive, the second strategy introduces sibling fixed-effects to observe the within-mother variation in the infant's health. This strategy controls for unobservable time-invariant characteristics of mothers and States, which may bias outcomes. Specifically, it controls for any confounding factors at the State level, such as health policy, or differences in children's obesity rates. This strategy has been used in other studies looking at in-utero shocks' impact on children's outcomes (Kudamatsu 2012, Majid 2015, Panda 2020).

The estimates suggest that, on average, in-utero exposure to the SSBs price decreased children's height but did not significantly reduce their weight, BMI, overweight, or obesity.

This paper will contribute to three bodies of knowledge. First, it is in line with the literature on the implications of the Fetal Origin Hypothesis that states that environmental and nutritional in-utero shocks have long-term effects on child growth (Gluckman 2004, Barker 1990, Lavy et al. 2016). Almond and Doyle (2011) study the impact of Ramadan in the US and finds that children exposed to fasting in-utero are smaller. Van Ewijk (2011) also find consequences for general health and a higher likelihood of heart problems and type 2 diabetes in adulthood for children exposed to Ramadan in-utero. Human capital and cognitive development are also affected. Majid (2015) shows that fasting during Ramadan reduces cognitive and math test scores by 7.17% and 8.4%, respectively. Neelsen and Stratmann (2011) find that children exposed to the Greek famine of 1941-1942 are less literate and pursued fewer years of education as adults. In the medical literature, the effects of consuming SSBs while pregnant are ambiguous. Azad et al. (2016) found no significant association between SSBs consumption and BMI in children. While Jen et al. (2017) find a positive association between consumption of the SSBs and children's BMI when excluding soda. This paper is different because it studies an in-utero shock from a policy, although it remains exogenous to pregnancy timing. It examines whether a tax policy can be a preventive measure for nutritional behavior and child health.

This paper also contributes to the literature on the effectiveness of "sin tax" on SSBs (Cawley et al. 2019). Aguilar et al. (2021) use a single database to estimate daily caloric consumption in Mexico. They find that the number of calories from taxed beverages decreased by 2.7% but was offset by the increase in other caloric products. In Catalonia, Fichera et al. (2021) use loyalty cards to estimate the effects of SSBs tax. They find a 2% decrease in sugar consumed in SSBs compensated by the "zero-sugar" drinks, which are less taxed. The same decline is observed in Chile and South Africa (Nakamura et al. 2018, Manyema et al. 2014, Stacey et al. 2021).

In South Africa, [Essman et al. \(2021\)](#) find that the demand for SSBs drops by 22% after the implementation of the tax, although they cannot claim a causal relationship. They use a sample of low-income and high SSBs consuming households who are more likely to be disproportionately affected by the “sin tax” ([Allcott et al. 2019](#)).

Finally, this paper adds to the literature estimating the impact of the tax on obesity in Mexico ([Hernández-Cordero et al. 2017](#)). [Gračner \(2021\)](#) links consumer food prices to obesity in Mexico. She finds that decreasing prices of sugar-rich foods explains about 15% of the obesity and diabetes rise between 1996 and 2010. Therefore, the price elasticity of demand may be a factor in nutritional and behavioral change. [Cawley \(2015\)](#) places the “sin tax” as a key preventive policy to fight obesity. [Grogger \(2017\)](#), and [Andalon and Gibson \(2017\)](#) predict the impact of the SSBs tax on the Mexican adult population, but the most accurate ones show a very small impact. [Gračner et al. \(2022\)](#) study the effect on adolescents and find that the tax would only affect adolescent girls who are obese.

The paper proceeds as follows. Section 2 presents the context of the SSBs tax, sugar consumption, in-utero shocks, and infant outcomes. Then, section 4 presents the data sets and gives summary statistics. The empirical strategies are introduced in section 5. Results are reported and discussed in section 6.

## 2 Background

SSBs consumption has become a health concern because of its positive association with obesity ([Organization 2015](#), [World Health Organization 2014](#)), due to its immediate increase in added sugar consumption ([Malik et al. 2013](#)) and its indirect impact on calories' intake from other food and beverages. Specifically, in Mexico, added sugars represented 12,5% of total energy consumed in 2012, 70% of which were coming from SSBs ([World Health Organization 2017](#), [Sánchez-Pimienta et al. 2016](#)). Additionally, SSBs, as energy-yielding clear liquid beverages, have a low satiety effect encouraging the consumption of other high-calorie foods or drinks ([DiMeglio and Mattes 2000](#), [Mattes 2006](#)).

Although SSBs consumption is strongly associated with increasing BMI for adults and children, its impact on infant is discussed. [Azad et al. \(2016\)](#) studied the intake of SSBs in the daily nutritional habits of a cohort of 3033 pregnant women in Canada. They found no effect for SSBs on BMI z-score or overweight risk among one-year old-infants. [Jen et al. \(2017\)](#) found a positive association between sugar-contained beverages during pregnancy and children’s BMI, which is not explained by soda<sup>1</sup>. However, as they followed a prospective cohort, from fetal life onward, of 3312 mother-child pairs in the Netherlands, the authors highlighted that intakes of soda may have been too low to detect potential associations. Earlier, [Englund-Ögge et al. \(2012\)](#) tracked SSBs consumption in a cohort of 60,761 pregnant women, reporting their intake from mid-pregnancy onward. The authors found a positive association between SSBs intake and women’s BMI and an increasing preterm delivery. Pregnant women’s obesity can increase the risk of obesity, heart disease, diabetes, and asthma in infants and reduce their cognitive performance ([Godfrey et al. 2017](#), [Heslehurst et al. 2019](#)). SSBs consumption may also impact height, as obese children are usually taller than normal-weight children ([Ajala et al. 2011](#)). [de Ruyter et al. \(2012\)](#) findings suggest that reducing SSBs decrease children’s height. Additionally, [Thomas and Strauss \(1992\)](#) found that rising sugar prices have already been the source of shrinkage in infants.

So far, taxing SSBs in Mexico has decreased SSBs consumption without changing the total energy intake in the general population. On January 1st 2014, Mexico’s Special Tax on Production and Services (*Impuesto Especial de Productos y Servicios –IEPS*) introduced a tax of one peso per liter on SSBs<sup>2</sup>, excluding non-added sugar drinks like fruit juices. As figure 1 illustrates, SSBs’ consumer prices in Mexico increased by about 12%, but differently across states (see figure A3.5), from a decrease of 2% to a pick at 18%. The tax directly affected purchase trends of sodas, energy drinks, juices, or flavored water. [Colchero et al. \(2016\)](#) found a decrease of 12mL/capita/day of SSBs, while untaxed beverages, notably bottles of water, increased by 36mL/capita/day. [Aguilar et al. \(2021\)](#) found a 2.7% decrease in SSBs calories purchased, but this was compensated by untaxed goods, such that

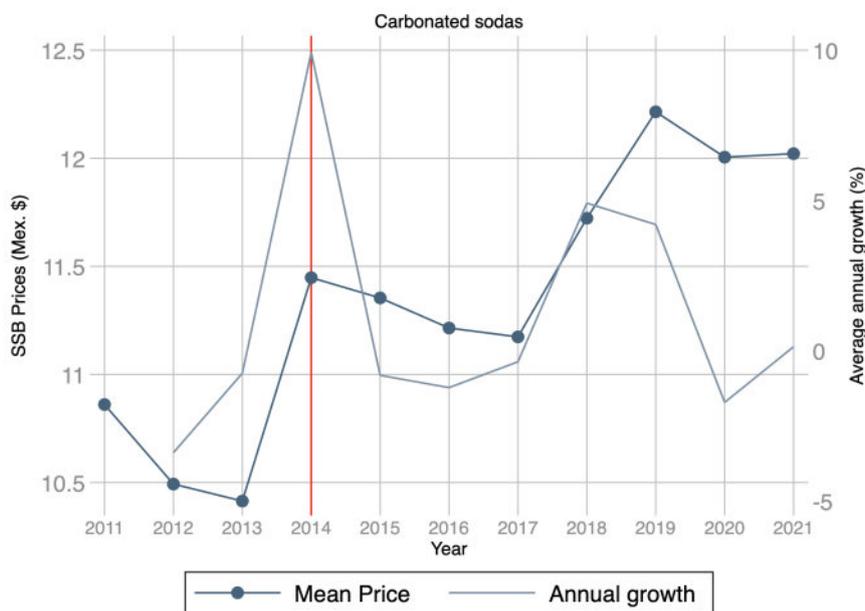
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<sup>1</sup>Sodas are the main beverages impacted by sin tax, specifically in Mexico.

<sup>2</sup>It equals 7.64 US cents at the time of reform, taking the exchange rate on December 31st, 2013.

total calorie intake did not change. Prices hikes reduced SSBs purchases by nearly 8% (Aguilar et al. 2021). However, no study has precised the tax impact on SSBs consumption of pregnant women in Mexico. Figure A3.1 shows that weekly consumption of SSBs has decreased over time for adults and women. Between 2012 and 2020, fewer people consumed SSBs seven days a week. More people reported never consuming them.<sup>3</sup> The kernel density (Figures A3.3) also shows that soft drink consumption is correlated with BMI in our sample, both in children and adults.

Figure 1: SSBs price variation at national level



Note: The graph plots the average annual price of carbonated SSBs and the average annual growth rate of SSBs prices between 2011 and 2021. The average annual price is based on the INEGI database, which gives the nominal prices of beverages sold at retail outlets (e.g., supermarkets, convenience or grocery stores, warehouse clubs, and street stalls) in 46 different cities with more than 20,000 inhabitants each month between 2011 and 2021. All taxes except the value-added taxes are included in the consumer prices. After selecting the carbonated drinks, the nominal price was deflated by the consumer price index specific to beverages, based on December 2011. The final annual average price is not weighted. The average annual growth rate of the price of carbonated SSBs peaked in 2014 at 10%.

### 3 Conceptual framework

Consuming SSBs is not the most optimal choice for health. Rather, SSBs consumption-related diseases and obesity illnesses are market failures with an

<sup>3</sup>Daily consumption patterns are less clear, but may be more subject to measurement error, as it is more difficult to estimate a consistent daily average

external cost for healthcare systems, as much as financial and health consequences at the individual level. Although it is reasonable to assume that individuals are aware of SSBs' health risks, one may argue there is some information asymmetry in the scale of those risks. This section presents the economic rationale behind the tax on SSBs.

Taxing SSBs is a way to internalize externalities from consuming energy-dense and nutrient-poor foods. The canonical economic model by (Cawley et al. 2019) shows that increasing SSBs prices would reduce the SSBs consumption if there is some price elasticity of the demand and if there exists a substitute to SSBs. The goal would be to encourage consumers to switch to healthier beverages such as bottled water. Before the tax, the opportunity cost of substitution may be too high. The introduction of the tax might have reduced the opportunity cost, and it took two years for inhabitants to switch to bottled water after the tax implementation. However, like in other low and middle-income countries, access to bottled water is not guaranteed to everyone in Mexico.

The literature on food insecurity and obesity can help define hypotheses on the impact of safe drinking water scarcity on SSBs consumption. Food insecurities imply biological and sociological mechanisms triggering obesity, respectively referred to as the insurance hypothesis (Nettle et al. 2017) and the resource scarcity hypothesis (Dhurandhar 2016). Martínez et al. (2020) highlight how scarcity and obesity are interdisciplinary topics and should be recognized at least. However, this study will focus on the socio-economic mechanisms exclusively. People facing food insecurity have limited purchasing power and face time, knowledge, and resource constraints. Thus, food insecurity increases the likelihood of buying ready meals, less nutritious and high-calorie foods, and decreases the likelihood of engaging in healthy nutrition and physical activity (Goldblatt et al. 1965, Dietz 1995). Dhurandhar (2016) states that the resource scarcity hypothesis “suggests that perceived food insecurity, in a permissive environment where there is access to high-calorie foods, may cause positive energy balance specifically in low social status individuals, but not in high social status individuals.”

The impact of the tax could depend on income too, all the more so [Colchero et al. \(2015\)](#) find that low-income households in marginalized areas have higher elasticities for SSBs. [Vega-Macedo et al. \(2014\)](#), [Ponce-Alcala et al. \(2021\)](#) give evidence of the positive relationship between food insecurity and obesity in Mexico. This relationship is stronger for Mexican women, specifically those of reproductive age ([Morales-Ruán et al. 2014](#), [Jones et al. 2017](#)). However, there is only evidence suggesting that safe drinking water scarcity and obesity illnesses, and SSBs consumption-related diseases might be related. [Gutierrez and Rubli \(2021\)](#) found that the introduction of the tax has increased the number of diarrheas in areas where inhabitants had no access to safe drinking water. The authors show descriptive evidence suggesting that inhabitants, aware of the poor water quality, adopted avoidance behavior. They would prefer to drink bottled beverages - including SSBs - than water or bottled water. Another study in Morocco finds that getting better access to piped water decreases children's overweight rates. Although [Ritter \(2021\)](#) does explore the channels, her literature suggests that the lack of water and the overconsumption of sodas as a substitute may increase children's BMI. This paper introduces empirical evidence to test a new hypothesis on the heterogeneous effect of the tax relative to safe drinking water scarcity and food insecurity.

## 4 Data

### 4.1 Data on health outcomes and cognitive development

Outcomes and control variables come from the ENSANUT database, a household survey on health and nutrition in Mexico. The INEGI (Mexico) conducted this survey from 2000 to 2020/21, but this study relies on four waves: 2012, 2016, 2018, and 2020/21. Households are selected at the primary stratification unit and geostatistical base area level. The ENSANUT database is representative at the national, urban/rural, and federal entities (States) levels and at the metropolis of Mexico City. From 2012 to 2020, the database gathered data on 130,534 households and 423,973 individuals. The surveys and sample sizes may vary yearly, but the sample structure and themes persist.

The main outcomes are anthropometric variables of weight, height, BMI z-score,

overweight, and obesity. Weight and height are given in the data set, while the BMI is calculated according to the formula  $Weight/Height^2$ . The last variable is standardized with *z**bmicat* Stata commands (Vidmar et al. 2013), meaning it is age- and sex-adjusted based on the World Health Organization Child Growth Reference data. The result is then converted into percentiles based on a standard normal distribution to capture child-specific anthropometric trends. The risk of being overweight or obese is a discrete variable that equals 1 if the child is in the 75th or 85th largest percentiles, respectively, and 0 otherwise.

The ENSANUT 2018 survey incorporates cognitive development questions. These variables provide information about children's behavior and learning. The second part of the analysis includes those outcomes, since sugar intake could impact infant cognitive development (Cohen et al. 2018).

The sample is restricted to children from 3 to 6 years old<sup>4</sup>, to keep children of similar ages and comparable BMI. The databases for 2012, 2016, and 2020 provide respondents' ages and dates of birth. The date is used to compute the number of months during which children were exposed to the reform in-utero. Additionally, a discrete variable equals 1 for children exposed to the price increase if their mothers were pregnant for at least two months after January 1, 2014, i.e. children born after February 28th, 2014. It equals 0 otherwise.

The exact date of birth of the children is not available for the 2018 sample.<sup>5</sup> The database provides the completed age in years and the age in months at the time of the survey. The exact date of interviews is not available for anonymity issues, but it is known that the interviews took place from July 30, 2018, to June 28, 2019. It is unclear whether children whose completed age indicates that they could have been born before or after February 28, 2014, were exposed to the tax reform. Treated or untreated status can be identified for most children aged 3-6 years in 2018 but not for children aged 54-60 months (4.5-5 years) as of July 30, 2018, which represent 2% of the final sample. I exclude these children from the sample to avoid any measurement error. As sample selection should be unrelated to the treatment

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<sup>4</sup>I keep this age range because it combines children of the same age whether they were born before or after 2014. There are no 7-year-old children born after 2014, and children under 3 are too young to compare their weight.

<sup>5</sup>The 2018 sample represents 24% of the total sample and 54% of exposed children.

or outcomes, the final estimates will not be biased.

The place of birth matters too, to define the exposure to SSBs' price increase since SSBs' price increase varies between states (see sub-section 4.2). The ENSANUT database gives the place of birth, except for the 2016 wave. It is assumed that the place of residence at the time of the interview is the place of birth. In the 2012, 2018, and 2020 samples, post-natal migration only accounts for up to 10% of the full sample of children, and 9.8% of the sample was reduced to families with two children born before and after 2014.

This survey accurately documents the health and nutrition behaviors of the Mexican population. Individuals were surveyed on common socio-demographics<sup>6</sup>, nutritional habits<sup>7</sup> and anthropometric characteristics at child and mother level<sup>8</sup>. Specifically, we include age (mother and child), rural or urban area at the time of the interview, school attendance (child), level of education (mother), salary, and marital status of the mother. There is no variable available for income. The parents' and child's nutritional and health behaviors impact the latter's weight and height. The database does not detail the health and dietary habits of the mother at the time of her pregnancy. However, the respondents describe their level of physical activity at the time of the survey. This variable captures the attitude towards physical health and certainly influences the child's growth. Although it does not measure sporting attitude variation over time, it is included as a covariate in the regression. The child's healthy behavior is estimated with a question on soda consumption in the week before the survey. This question is not asked to all children in the sample and is not available for 2016. It will only be used for heterogeneity analyses.

Table 1 presents the anthropometric outcomes and the socio-demographic characteristics of children and mothers. It details the weight of each survey in the final sample. Children exposed in-utero to the reform are smaller and less fat.

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<sup>6</sup>Main variables collected are age, gender, education, marital status, employment, income, and expenditures.

<sup>7</sup>Respondents were asked to report their physical activity and their consumption habits in the week before the survey.

<sup>8</sup>Not all individuals are surveyed, but for more details, please refer to the various explanatory documents available on INEGI website.

They have a lower probability of being overweight. These parameters are certainly related to age since many children exposed to in-utero are younger. Exposed children have a lower BMI z-score, although the variable is adjusted for age and sex. Regarding covariates, children born after 2014 attended school less and had a higher probability of living in rural areas. Mothers of in-utero exposed children are younger, less educated, less often in couples, and work more in the previous week. They are less active in sports than mothers of children not exposed in-utero. The different samples may explain the differences in socio-demographic determinants between exposed and unexposed children. The main regressions will include fixed effects for each survey cohort to control this possible bias.

Table 1: Summary statistics - child variables (full sample)

	All		Non Exposed		Exposed		Diff.	
	Mean	Obs.	Mean	Obs.	Mean	Obs.	<i>t</i> -test	Obs.
Weight (kg)	18.21	3972	18.65	3204	16.38	768	2.272***	3972
Height (cm)	105.84	3972	107.03	3204	100.89	768	6.142***	3972
BMI z-score	0.43	3972	0.45	3204	0.36	768	0.095**	3972
Obese	0.05	3972	0.05	3204	0.04	768	0.007	3972
Overweight or obese	0.16	3972	0.17	3204	0.12	768	0.046***	3972
Age	4.53	3972	4.69	3204	3.82	768	0.873***	3972
Gender	1.50	3972	1.50	3204	1.51	768	-0.006	3972
Is currently at school	0.61	3820	0.60	3052	0.66	768	-0.068***	3820
SSB consumption per days in a week	2.50	1002	2.48	523	2.52	479	-0.044	1002
Rural	0.48	3972	0.52	3204	0.32	768	0.208***	3972
Age (mother)	29.81	3532	29.98	2959	28.93	573	1.048***	3532
Education Grade (mother)	3.38	3144	3.39	2918	3.20	226	0.194**	3144
Worked previous week (mother)	0.26	3532	0.24	2959	0.37	573	-0.134***	3532
Sport activity previous week (mother)	0.22	1402	0.24	862	0.20	540	0.045**	1402
In a relationship (mother)	0.77	3532	0.84	2959	0.45	573	0.387***	3532
Survey 2012	0.57	3972	0.71	3204	0.00	768	0.708***	3972
Survey 2016	0.09	3972	0.11	3204	0.00	768	0.110***	3972
Survey 2018	0.24	3972	0.17	3204	0.55	768	-0.378***	3972
Survey 2020	0.10	3972	0.01	3204	0.45	768	-0.439***	3972

Note: \*\*\*  $p < .01$ , \*\* $p < .05$ , \*  $p < .1$  The table reports the sample means of child-level variables. Column “All” is for the whole sample of children aged 3 to 6, for whom BMI is available, and exposure status is available. Columns “Exposed” and “Non Exposed” report the average of the main outcome means for children born before or after February 28th, 2014 (see sub-section 4.1 for more details on the date). Column “Diff.” gives the *t*-statistics testing if the mean significantly differs between before and after the SSBs’ price increase of January 1st, 2014. BMI z-score is based on raw BMI adjusted to age and gender with the WHO Child Growth Standards and WHO reference 2007 composite datafiles (Vidmar et al. 2013). The result is then converted into percentiles based on a standard normal distribution to capture child-specific anthropometric trends. The risk of being overweight or obese is a discrete variable that equals 1 if the child is in the 75th or 85th largest percentiles, respectively, and 0 otherwise. SSBs consumption gives the number of days of children’s SSBs consumption during the week before the interview. Rural indicates the place of residence during the interview. Mothers’ education grade gives the highest level of the school attended. The mother’s professional status would equal 1 if she worked at least one hour before the interview and 0 if she did not work at all. A relationship is a discrete variable that equals 1 if the mother is married or cohabiting.

Children’s interviews reveal whether they live with their mothers. Thanks to this question, I connect siblings from the same mother and later include mother-fixed effects. The tax effect is captured by within-mother variation, using children aged 3 to 6 from mothers who gave birth before and after the tax, compared to mothers with two or more children exclusively before or after February 28th, 2014.

The sample is restricted to children aged 3 to 6 to reduce the risk of omitted time-varying variables. The hypothesis is that the number of variables explaining weight, height, overweight, and obesity increase with age, including physical activity, nutritional habits, occupation, or student status. However, physical activity and nutritional habits cannot be used, as they are available for only a small sample in 2018. Restricting the sample may lead to possible selection in birth spacing and reduce the sample to the 2018 wave (birth year between 2012 and 2015). Women with siblings with one to three years difference may differ from women with siblings with more than three years difference in fertility or socio-economic determinants. Additionally, the final sample may include only children surveyed in 2018, since only children born between 2012 and 2015 are kept.

Table 2 presents mothers' characteristics from three different samples. Mothers are split into three groups: (1) those who had kids strictly before or strictly after the implementation of the tax but no siblings born before and after; (2) mothers with two or more kids exclusively before and after but whose one or both children are older than 6<sup>9</sup>; (3) mothers with two or more children born before and after February 24th, 2014 who are aged between 3 and 6. Table 2 tests the representativity of the sample used for the mother-fixed effects specification. The first t-test compares mothers from group (1) to those from group (3). Mothers in group (3) are a little less educated than the mothers surveyed in group (1). Plus, they are less in a relationship. The second t-test compares mothers from the sample to mothers who have siblings born before and after the tax, including siblings older than 6 years old. Women in the final sample are two years younger on average, compared to women with siblings with at least one older than 6. This difference may not jeopardize the representativity of the sample used in the mother-fixed effects strategy.

Table A3.1 shows the difference in height, weight, BMI, overweight, and obesity is more important between siblings born before and after than in siblings born exclusively before or after. This gap might be related to age difference despite BMI, overweight, and obesity being adjusted for age and gender.

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<sup>9</sup>Those children are excluded from the sample used for the mother-fixed effects specification.

Table 2: Summary statistics - mother variables

	(1)		(2)		(3)		(4)	(5)
	Siblings born before or after		Siblings born bf and aft aged > 6		Siblings born bf and aft aged 3 to 6		Diff. (1) - (3)	Diff. (2) - (3)
	Mean	SD	Mean	SD	Mean	SD	<i>t</i> -test	<i>t</i> -test
Age	29.53	5.94	31.28	4.54	29.39	6.07	0.142	2.618***
Education Grade	3.31	1.58	3.19	1.47	3.13	1.39	0.185**	0.051
Work previous week (at least one hour)	0.28	0.45	0.32	0.47	0.30	0.46	-0.020	-0.003
In a relationship	0.70	0.46	0.53	0.50	0.47	0.50	0.227***	0.045
Sport activity in the previous week	0.22	0.41	0.14	0.35	0.21	0.41	0.004	-0.057
SSB consumption per days in a week	2.46	1.31	2.56	1.29	2.51	1.31	-0.049	0.031
Year survey 2012	0.49	0.50	0.00	0.00	0.00	0.00	0.494***	0.000
Year survey 2016	0.08	0.28	0.00	0.00	0.00	0.00	0.083***	0.000
Year survey 2018	0.35	0.48	0.56	0.50	0.93	0.26	-0.582***	-0.363***
Year survey 2020	0.08	0.27	0.44	0.50	0.07	0.26	0.004	0.363***
Observations	4069		136		575		4644	632

Note: \*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .1$ . The table reports summary statistics of mothers' characteristics, including age, education grade, whether the respondent worked in the previous week, whether the respondent is in a relationship, whether the respondent had a physical activity in the previous week and how many days a week the respondent consumes SSB. Mothers' education grade gives the highest level of the school attended. The mother's professional status would equal 1 if she worked at least one hour before the interview and 0 if she did not work at all. In a relationship is a discrete variable equal to 1 if the mother is married or cohabiting. Sport activity would equal 1 if the respondent practiced at least one hour of sport over the past week. This variable is not available in the 2012 and 2016 ENSANUT waves. Column (1) details the mean and standard deviation for respondents who had kids strictly before or after the implementation of the tax but no siblings born before and after. Column (2) reports the same descriptive statistics for mothers with two or more kids exclusively before and after but whose one or both children are older than 6. For this reason, those children are excluded from the sample. Column (3) gives the sample mean for mothers with two or more children born before and after February 24th, 2014, who are aged between 3 and 6. They are the treated group of the final sample in the mother-fixed effects estimation. Columns (4) and (5) give details on the representativity of the sample (3). Column (4) compares the characteristics of the sample (1) to (3), and Column (5) compares the characteristics of the sample (2) to (3).

## 4.2 Data on prices

The identification strategy will take advantage of the price variation across states to observe the impact of the tax on health outcomes. The Mexican law set an excise tax of one peso per liter of SSBs. Although most countries choose this strategy, few governments set ad valorem taxes, i.e., the percentage of a retail price, which ensures a uniform tax rate across the country. With an excise tax, producers and retailers decide the rate to which they increase the consumer price (see the country review by [Cawley et al. \(2019\)](#)). The price increase varies according to the relative elasticity of the local supply and demand.

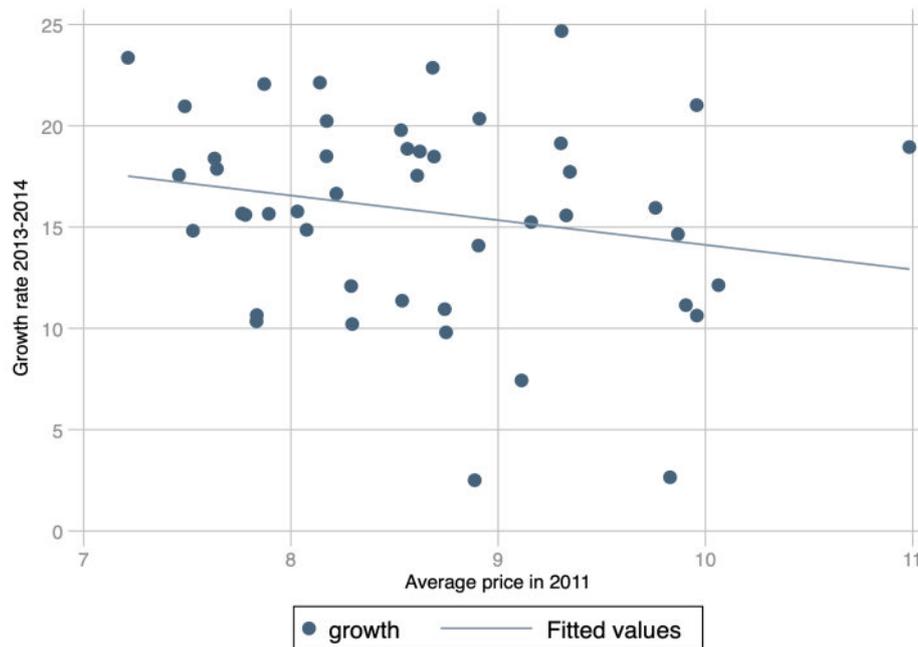
The INEGI records consumer prices (nominal prices) at retail outlets (e.g., supermarkets, convenience or grocery stores, warehouse clubs, and street stalls) in 46 cities with more than 20,000 inhabitants each month between 2011 and 2021. Prices include taxes, such as Mexico's Special Tax on Production and Services, but not

Value Added Tax. It is, therefore not known to what extent the price increase is linked to the tax increase. SSBs' price variation before and after the tax implementation is measured using the strategy by [Andalon and Gibson \(2017\)](#), [Gračner et al. \(2022\)](#). Products are tracked using a unique identifier and a barcode that details the product composition (product name, brand name, packaging, and weight). This information makes it possible to distinguish between products subject to tax (those with added sugar) and those exempt from tax.<sup>10</sup> There are 826 beverages subject to the tax, the majority of which are carbonated drinks. The price evolution is then restricted to carbonated beverages, available in all cities, as opposed to non-carbonated drinks with added sugar (e.g., flavored water). Plus, [Grogger \(2017\)](#) show that the price of soda has increased by more than the proportion of the tax without the substitute goods necessarily having increased. Then, prices are deflated using the 2011 Mexican consumer price index for beverages to obtain the real value. Eventually, SSBs prices are averaged yearly at the regional and national levels.

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<sup>10</sup>The taxed products are: “non-alcoholic beverages with added sugars (except medical beverage products), such as carbonated SSBs (i.e., soft drinks or regular sodas), non-carbonated SSBs (i.e., industrialized juices, flavored waters, or Aguas Frescas), as well as energy drinks, powders and concentrates.

Figure 2: SSBs price variation 2013-2014 by price average in 2011



Note: The graph plots the regional SSBs prices' growth rate from 2013 to 2014 relative to the regional average prices in 2011. It shows a negative association between the level of prices in 2011 and the price change after the implementation of the tax on SSBs. The sample is restricted to carbonated beverages. INEGI records consumer prices (nominal prices) at retail outlets (e.g., supermarkets, convenience or grocery stores, warehouse clubs, and street stalls) in 46 cities with more than 20,000 inhabitants each month. Prices are deflated using the 2011 Mexican consumer price index for beverages (base December 2011) to obtain the real value and are averaged yearly at the regional levels.

SSBs' prices are collected at the city level and averaged at the state level to be matched with households. The state is the only information available about their location. The INEGI database does not share the exact locality. Note that prices vary even at the city level between neighborhoods. [Campos-Vázquez and Medina-Cortina \(2019\)](#) highlight that the variation in competition over a 2-5km bandwidth is enough to change the price of soda. Further study could estimate the variation in competition with the retailers' geolocation from the database of *Directorio Estadístico Nacional de Unidades Económicas*.

After the tax implementation in 2014, SSBs' price hike (figure 1) was significantly higher than any other beverages (see figure A3.7) or than the average annual growth in 2013 or 2015 (see figure A3.5). As Figure A3.4 shows, SSBs' prices increased differentially across cities. [Campos-Vázquez and Medina-Cortina](#)

(2019) explained that prices increased less in more competitive markets. They find that the increase in competition, as measured by the number of shops within a radius of 2-5km, is associated with a decrease in price variation at the time of the implementation of the tax. This effect is not constant across the intensity of competition. Prices vary more in areas with little competition than in those with more competition, with retailers taking advantage of the low price elasticity where supply is weakest. The figures show a negative relationship between SSBs prices in 2011 and their average annual growth rate in 2013-2014 and 2020, respectively.

The law implemented on January 1, 2014, extended beyond sodas to include other sugary drinks. Section 4.2 describes the methodology to reduce the SSBs' prices to sodas' prices. One could argue that this choice leaves out other beverages affected by the tax. Figure A3.7 shows that other beverages' prices did not hike after the tax implementation. Another tax was implemented on the same but on food that could have impacted our outcomes. However, Aguilar et al. (2021) did not find an impact on the consumption of food targeted by the tax.

## 5 Empirical analysis

This paper uses three identification strategies to investigate the SSBs tax's impact on infant's health outcomes. The introduction of a one-peso excise per liter of SSBs aimed at increasing SSBs' prices. Yet, although the tax was uniform across the country, it led to heterogeneous price increases (see figures A3.4 and A3.5). Additionally, the timing of childbirth and the length of the pregnancy changes mothers' exposure to price increases.

Thus, the first strategy takes advantage of the treatment intensity with two continuous variables. One variable captures the months of exposure, and another one measures the SSBs price growth rate between 2013 and 2014 at the regional level. This strategy estimates the intensive margin and overcomes pitfalls of the canonic two-way fixed effect recently highlighted in the literature (Callaway et al. 2021). However, in this case, since the law was implemented at one point in time, the two-way fixed effect could be used to estimate the impact of the mere exposure to the SSBs price increase without risking biases resulting from a time-staggered

treatment. The second strategy uses dummies to measure the extensive margin of the SSB price increase on children's health outcomes, similarly to [Gračner et al. \(2022\)](#). Eventually, the last strategy aims at strengthening the internal validity of the results. It takes advantage of the structure of the sample to include mother-fixed effects which strengthens the internal validity of the results.

### *Event study*

Figure 3 presents an event study of in-utero exposure to the tax on BMI, overweight, and obesity. The plotted estimates depict the differential trends in children's BMI over 12 years before and after the tax implementation. The estimates are derived from the following regression.

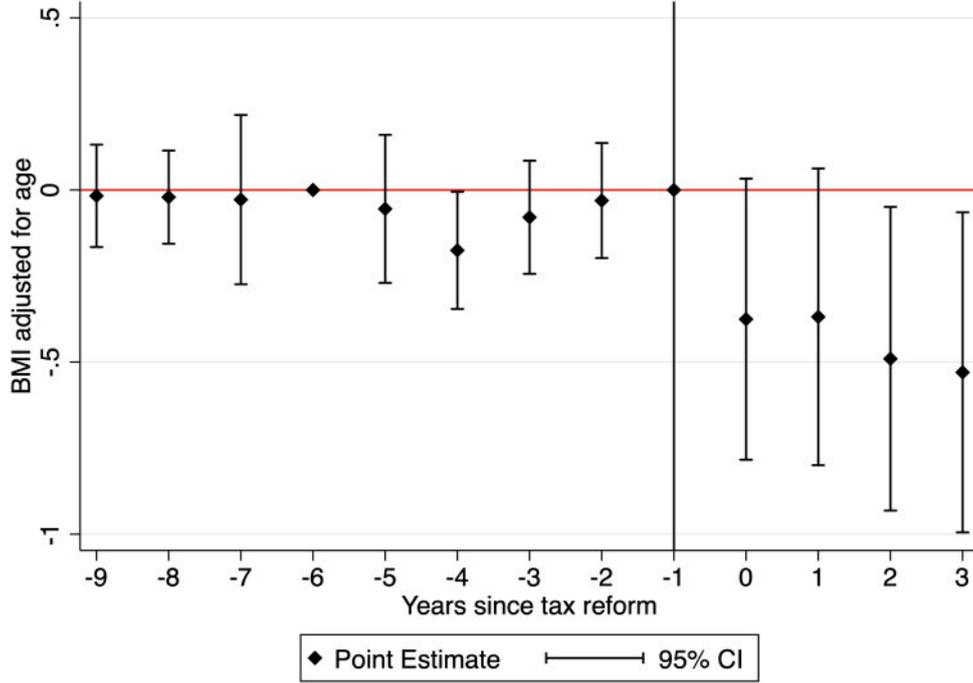
$$Y_{i,a} = \alpha + \beta_1 age + \beta_1 Exposure_i + \sum_{j=-9}^3 \gamma_j T_{2014+j} + \beta_3 X'_i + \epsilon_{i,a} \quad (1)$$

Control variables include age, school attendance, child gender, mother's employment and marital status, and living in a rural area. After the implementation of the tax, there is a fall in BMI, but not in the likelihood of being overweight or obese<sup>11</sup>, without pre-trend before 2014. This first analysis of the effect of the SSBs' price increase shows a temporal variation in BMI without the possibility of comparing it to a control group after implementing the tax.

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<sup>11</sup>See figures 3 and A3.2 that show a decrease in the probability of obesity and overweight before and after the implementation of the tax.

Figure 3: Children BMI before and after 2014



Note: The graph presents the estimates of children's BMI,  $\gamma_j$ , from the equation:  $Y_{i,a} = \alpha + \beta_1 age + \beta_2 Exposure_i + \sum_{j=-9}^3 \gamma_j T_{2014+j} + \beta_3 X'_i + \epsilon_{i,a}$ . The sample includes kids aged 3 to 6. The red line at  $t - 1$  indicates 2013, the year before the tax implementation, which is omitted. The dots represent the fall in BMI. The arrays represent the upper and lower confidence intervals of the estimates.

### Intensive margin

Two sources of variation determine mothers' exposure to tax-induced SSBs' price increase: the period of pregnancy and the state of residency during pregnancy. Pregnancies are exogenous to the implementation of the tax on January 1st 2014 and to the geographic variation of SSBs' price increase afterward. Similarly to [Rentería \(2022\)](#) and [Kuecken et al. \(2021\)](#), the following specification takes advantage of this exogenous variation in exposure:

$$Y_{i,s,a,t} = \alpha + \beta_1 (Prices_s^{2013-14} \times Exposedinutero_{i,s}) + \beta_2 Prices_s^{2013-14} + \beta_3 Exposedinutero_{i,s} + \beta_4 X'_{i,s,a,t} + \delta_s + \delta_{a,t} + \epsilon_{i,s,a,t} \quad (2)$$

Where  $Y_{i,s,a,t}$  is one of the health outcomes - weight, height, obesity, overweight, BMI detailed in section 4.1 - for a child  $i$  aged  $a$  in months, surveyed in year  $t$ ,

and whose mother was pregnant in a state  $s$ .  $Exposedinutero_{i,s}$  represents the number of months of children's in-utero exposure to SSBs price variation. Without accurate data on pregnancy, I cannot use the real length of gestation. It is assumed that all pregnancies lasted 266 days on average. The gestation length may be shorter or longer and thus impact the outcomes. Although this limit cannot be dismissed or its impact assessed, this element could be explored in future research.  $Prices_s^{2013-14}$  gives the average annual growth between 2013 and 2014 at the state  $s$  level. As figure A3.6 shows, SSBs price variation is endogeneous with former prices and is associated with local market characteristics such as the degree of competition (Campos-Vázquez and Medina-Cortina 2019) or retailers' size. This risk of endogeneity is tested later with robustness checks. The vector  $X'_{i,s,a,t}$  stands for a set of covariates: rural/urban area, child's school attendance, gender, mother's physical activity, mother's marital status, and mother's age. The terms  $\delta_s$  and  $\delta_{a,t}$  are state and age-per-survey-year fixed effects to control for potential time-invariant omitted variables.

#### *Extensive margin*

While equation 2 investigates the intensive margin, equation 3 estimates the extensive margin of the tax impact. Exposure to the tax is redefined as a discrete variable that equals 1 for in-utero exposure in its first to the seventh month, as when the tax was implemented on January 1, 2014. The variable equals 0 for pregnancies in the eighth month or if the child is already born. More precisely, children born up to February 28, 2014, are not considered exposed to the law, and the variable is then equal to 0.  $Exposurechildbirth_{i,s}$  is interacted with a discrete variable,  $HighPrices_s$ , which equals 1 if the State of birth was exposed to a high price increase and 0 otherwise. Following Gračner et al. (2022), a state is exposed to a high price increase if the growth rate in 2013-2014 is higher than 10%. Although setting a threshold may seem arbitrary, 10% is close to the average SSBs price increase of 12.5% between 2013 and 2014. Gračner et al. (2022) propose a second threshold at 5%. I discuss other thresholds at 8% and 12% in section 6.2.

$$Y_{i,s,a,t} = \alpha + \beta_1(HighPrices_s \times Exposurechildbirth_{i,s}) + \beta_2 HighPrices_s + \beta_3 Exposurechildbirth_{i,s} + \beta_4 X'_{i,s,a,t} + \delta_s + \delta_{a,t} + \epsilon_{i,s,a,t} \quad (3)$$

*Mother-fixed effects*

The first specifications use a sample of children surveyed at different points in time, assuming that each sample's error term would be equal. This could bias estimates, despite year-fixed effects. Previous estimations are threatened by time-invariant unobservable variables in mothers' nutritional habits or physical activity before and during pregnancy, which cannot be controlled with available data. Similarly to [Kudamatsu \(2012\)](#), [Majid \(2015\)](#), [Panda \(2020\)](#), equation 4 includes a mother-fixed effects  $\delta_m$  that allows comparison of children from the same mothers exposed to the tax to those who have not, respectively. Adding mother-fixed effects  $\alpha_m$  controls for time-invariant mothers' characteristics under a double assumption. First, the timing of pregnancies is exogenous to the tax implementation date. Second, the fixed effect captures only mothers' habits that have not changed from one pregnancy to another. This strategy reduces the omitted variable bias but at the expense of the coefficient precision.  $Exposedinutero_{i,s,m}$  is a binary variable equal to one if born after 2014, and  $HighPrices_s$  is a binary variable equal to 1 if the variation in price is larger than 10%. The equation is estimated over the sample of children whose mothers have at least two children between 3-6 years old.

$$Y_{i,s,a,m} = \alpha + \beta_1(HighPrices_s \times Exposedinutero_{i,s,m}) + \beta_2 HighPrices_s + \beta_3 Exposedinutero_{i,s,m} + \beta_3 X'_{i,s,a,m} + \delta_m + \delta_s + \delta_a + \epsilon_{i,s,a,m} \quad (4)$$

## 6 Results and discussion

### 6.1 Main results

Table 3 presents estimates of exposure to SSBs' price increases on children's outcomes.

Table 3: Main results

	Height	Weight	BMI	Overweight	Obese
	(1)	(2)	(3)	(4)	(5)
<i>Panel A: Intensive margin</i>					
Exposed in-utero (months of pregnancy)	-0.076 (0.126)	-0.001 (0.081)	0.020 (0.029)	0.006 (0.009)	0.004 (0.006)
Price increase (annual growth rate)	0.085 (0.649)	0.083 (0.418)	0.038 (0.147)	-0.015 (0.048)	-0.013 (0.031)
Exposed in-utero x Price increase	-0.003 (0.007)	0.003 (0.005)	0.001 (0.002)	0.000 (0.001)	0.000 (0.000)
Observations	3189	3189	3179	3189	3189
R2	0.660	0.392	0.032	0.026	0.024
Survey's year FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Mother FE	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>
<i>Panel B: Extensive margin</i>					
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	-3.005*** (0.575)	-0.839** (0.374)	0.078 (0.132)	0.005 (0.028)	0.063 (0.043)
Price increase (= 1 if annual growth rate > 10%)	0.637 (3.867)	0.092 (2.515)	0.018 (0.886)	-0.115 (0.186)	-0.167 (0.289)
Exposed in-utero x Price increase	0.018 (0.412)	-0.309 (0.268)	-0.111 (0.095)	-0.011 (0.020)	-0.039 (0.031)
Observations	3250	3250	3240	3250	3250
R2	0.665	0.395	0.033	0.024	0.028
Survey's year FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Mother FE	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>
<i>Panel C: Mother Fixed Effect</i>					
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	-2.851*** (0.599)	-1.083*** (0.358)	0.040 (0.133)	-0.021 (0.029)	-0.006 (0.046)
Price increase (= 1 if annual growth rate > 10%)	3.195 (2.951)	1.413 (1.758)	-0.056 (0.650)	-0.018 (0.143)	0.224 (0.226)
Exposed in-utero x Price increase	1.192 (0.734)	0.724* (0.439)	0.011 (0.163)	0.031 (0.036)	0.038 (0.057)
Observations	3756	3752	3743	3752	3752
No. of mothers	2662	2660	2655	2660	2660
R2	0.863	0.696	0.007	0.014	0.030
Survey's year FE	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>
Mother FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>

Note: \*\*\* p < .01, \*\* p < .05, \* p < .1 Standard error is in parenthesis. All regressions control for rural/urban areas, child's school attendance, gender, mother's physical activity, mother's marital status, and mother's age. Panel A and B sample includes any child aged 3 to 6, born before or after Jan. 1st, 2014. The sample is restricted to children for whom the BMI z-score is available. The coefficient of interest in Panel A is  $Prices_s^{2013-14} \times Exposure_{i,s}$ . In this sample,  $Prices$  is the SSBs price growth rate between 2013 and 2014 in the real term.  $Exposure$  is the number of months of pregnancy after Jan. 1st, 2014. Panel A gives the Average Treatment Effect as an intensive margin. The coefficient of interest in Panel B is  $Prices_s \times Exposure_{i,s}$  where  $Price$  is a binary variable that equals 1 if the child is born after Feb. 28th, 2014.  $Exposure$  is a binary variable that equals 1 if child  $i$  was born in a State where the SSBs prices increased by more than 10% in 2013-2014. Panel C sample includes any child aged 3 to 6, born before or after Jan. 1st, 2014. The sample is restricted to children living in households with 2 or more siblings, for whom BMI z-score is available. The regression adds mother-fixed effects. The coefficient of interest is the interaction between  $Exposedin - utero_{i,s,m}$  and  $Prices_s$  that equals 1 for children born after Feb. 28th, 2014.

*Intensive margin impact of the tax*

The upper part of the table does not show any significant effect of being exposed to SSBs' price increases during pregnancy. Not only the interaction term is not significant, but neither is the number of months of exposure (*Exposed in utero*) or the average growth rate of SSBs prices (*Price increase*).

*Extensive margin impact of the tax*

Panel B of table 3 shows that the coefficient of the interaction term is not significant for none of the outcomes. However, being born after February 28, 2014, led to a 3.005 centimeters decrease in height and a 0.839 gram decrease in weight.

*Mother-fixed effects*

The bottom part of table 3 presents the results of the estimation of the mother-fixed effect. The coefficient of interest is not significant for any of the outcomes. Children born after the tax implementation are significantly smaller by 2.851 centimeters and lighter by 1.083 kilograms, certainly as they are younger.

The outcomes, specifically BMI, overweight, and obesity, depend on multiple determinants such as nutrition beyond SSBs, physical activity, or the daily environment. Estimates are consistent with previous research showing a small impact of the tax on health outcomes. [Andalon and Gibson \(2017\)](#) find that the SSBs tax would reduce weight by 0.545 kilograms on average after correcting the price elasticity of demand estimated by [Grogger \(2017\)](#). [Gračner et al. \(2022\)](#) find a small impact of the price increase on adolescents' BMI. An increase of the tax by more than 10 percent decreased the BMI of adolescent girls with a BMI at or above the 75th percentile pretax by 0.59 percentile.

## 6.2 Robustness

*SSBs price threshold at 10%*

Table A3.3 presents estimates with alternative thresholds: 8% and 12%. The table shows that exposure to a price increase higher or equal to 8% significantly reduces children's weight, BMI, overweight, and obesity in the mother-fixed effects

regression but not in the extensive margin one. Plus, the interaction term of interest has no significant impact on none of the other coefficients. The price increase has no more significant impact once the threshold is at 12%. These results bear out the sensitivity of the threshold although there is no difference in the interaction variable that should measure the effect of the tax.

#### *Sampling and Mexico City*

Mexico City is the capital of Mexico. It is likely that this region has a particular weight in the distribution due to its population size. In addition, the characteristics of the market must be particularly different from the rest of the country. I removed Mexico City from the sample. Table A3.4 finds that the jackknife analysis does not substantially change the results compared to the main results.

#### *Mothers' habits between the tax implementation and the pregnancy*

One concern is that mothers may change their behavior before the pregnancy as soon as they are exposed to the SSBs' price increase. Mothers could change their SSBs consumption, which would affect their own health outcomes through new nutritional habits and, afterward, the infant. As some mothers may give birth several months after the tax implementation, the variable *Exposed in utero* in specification 2 would underestimate the distribution of the time of exposure. An alternative would be to redefine the intensive margin as the number of months between January 1, 2014, and childbirth. The number of months is set at 0 for the control group. As the relationship between the number of months of exposure and the outcomes may be non-linear, I use linear and quadratic term. Table 4 presents the new estimates. The sample excludes kids interviewed in 2018 as the database does not provide the exact birth date. There is no significant impact of the interaction term, except the coefficient for height that significantly increases the height by 0.005 centimeters. The latter is not robust to the quadratic regression. Estimates also show that one additional month significantly decreases the height between 0.354 and 0.512 centimeters and the weight between 0.093 and 0.176 kilograms.

Table 4: Robustness - Months between the tax and the childbirth

	Height	Weight	BMI	Overweight	Obese
	(1)	(2)	(3)	(4)	(5)
<i>Linear regression</i>					
Months between the tax and the childbirth	-0.354*** (0.041)	-0.093*** (0.027)	0.009 (0.009)	-0.001 (0.002)	0.004 (0.003)
Price increase (annual growth rate)	-2.059 (1.877)	0.021 (1.239)	0.269 (0.422)	0.033 (0.088)	0.063 (0.135)
Months x Price increase	0.005** (0.002)	-0.000 (0.001)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Observations	1798	1798	1788	1798	1798
R2	0.651	0.371	0.041	0.035	0.043
Survey's year FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Mother FE	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>
<i>Quadratic regression</i>					
Months between the tax and the childbirth	-0.512*** (0.037)	-0.176*** (0.025)	-0.002 (0.009)	0.000 (0.003)	-0.000 (0.002)
Square of months between the tax and the childbirth	-0.001 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Price increase (annual growth rate)	-1.692 (1.821)	0.169 (1.227)	0.276 (0.422)	0.067 (0.135)	0.034 (0.088)
Square of months x Price increase	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Observations	1798	1798	1788	1798	1798
R2	0.672	0.385	0.042	0.044	0.035
Survey's year FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Mother FE	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>

Note: \*\*\* p <.01, \*\*p <.05, \* p <.1 Standard error is in parenthesis. All regressions control for rural/urban areas, the child's school attendance, gender, mother's physical activity, marital status, and age. The sample includes any child aged 3 to 6, born before or after Jan. 1st, 2014, and is restricted to children for whom the BMI z-score is available. The sample excludes children interviewed in 2018, for which the exact birth date is unavailable. The top part of the table, the linear regression, presents the estimates of the following regression  $Y_{i,s,a,t} = \alpha + \beta_1(\text{Monthstax} - \text{childbirth}_{i,s} \times \text{Prices}_s^{2013-14}) + \beta_2 \text{Prices}_s^{2013-14} + \beta_3 \text{Monthstax} - \text{childbirth}_{i,s} + \beta_4 X'_{i,s,a,t} + \delta_s + \delta_{a,t} + \epsilon_{i,s,a,t}$ . The coefficient of interest is  $\text{Months}_{i,s} \times \text{Prices}_s^{2013-14}$ . In this sample,  $\text{Prices}$  is the SSBs price growth rate between 2013 and 2014 in the real term.  $\text{Months tax-childbirth}$  is the number of months between January 1, 2014, and childbirth. The bottom part of the table, the quadratic regression, presents the estimates of the following regression  $Y_{i,s,a,t} = \alpha + \beta_1(\text{Monthstax} - \text{childbirth}_{i,s} \times \text{Monthstax} - \text{childbirth}_{i,s} \times \text{Prices}_s^{2013-14}) + \beta_2 \text{Prices}_s^{2013-14} + \beta_3 \text{Monthstax} - \text{childbirth}_{i,s} \times \text{Monthstax} - \text{childbirth}_{i,s} + \beta_4 \text{Monthstax} - \text{childbirth}_{i,s} + \beta_5 X'_{i,s,a,t} + \delta_s + \delta_{a,t} + \epsilon_{i,s,a,t}$ .

### *Time and unit-constant variables - Mothers' habits between pregnancies*

Without accurate data on the time of pregnancy, I cannot use the real size of gestation. It is assumed that all pregnancies lasted 266 days on average. The gestation length may be shorter or longer and thus impact the outcomes. Although this limit cannot be dismissed or its impact assessed, this element could be explored in future research.

The second empirical strategy uses the mother-fixed effects and assumes that mothers' characteristics impacting the outcomes' variation between siblings are

time-invariant. However, mothers could change their health behavior from one child to the next, whether in physical activity or nutritional habits. The database does not collect information on potential time-varying variables before or during pregnancy and I cannot control for mothers' time-varying variables between two pregnancies. I use the birth order-fixed effect to control for mothers' time-invariant omitted variables between two subsequent births. The assumption is that the trend in beverage habits may be comparable from one kid to another and across mothers. Although it is the best option currently used in the literature ([Panda 2020](#), [Majid 2015](#)), this variable is limited too, as it may confuse the number of kids for fertility. Table [A3.5](#) finds no significant effect once the birth rank is added to the mother-fixed effects.

*Time and unit-constant variables - Price variation within region*

SSBs' prices are collected at the city level and averaged at state-level to be matched with households, for which the state is the only information available about their location. The INEGI database does not share the exact locality. It could be argued that this method ignores possible variations within states. Prices vary even at the city level, between neighborhoods. [Campos-Vázquez and Medina-Cortina \(2019\)](#) highlight that the variation in competition over a 2-5km bandwidth is enough to change the prices of soda. Further study could estimate the variation in competition with the retailers' geolocation from the database of *Directorio Estadístico Nacional de Unidades Económicas*.

*Measuring height and weight*

Height and weight are the only outcomes significantly impacted by the tax in table [3](#). Table [A3.2](#) reports estimates using the height and weight z-scores. The coefficients are still significantly negative. The height z-score is the standard deviation above or below the mean of WHO standards size by age and gender. Using either the extensive margin or the mother-fixed effects, kids born after February 28th, 2014, are, on average, 0.61 standard deviations under the average WHO standard. Exposure also reduces weight by an average of 0.941 kilograms compared to the average Mexican child. Taking the average WHO standard, children born after the price rises are 0.355 standard deviations below the extensive

margin and 0.404 for the mother-fixed effects. However, the number of months during which the children are exposed in-utero has no significant impact on any anthropometric outcomes.

#### *Omitted variables*

The law implemented on January 1, 2014, extended beyond sodas to include other sugary drinks. Section 4.2 describes the methodology to reduce the SSBs' prices to sodas' prices. One could argue that this choice leaves out other beverages affected by the tax. Figure A3.7 shows that other beverages' prices did not hike after the tax implementation. Another tax was implemented on the same but on food that could have impacted our outcomes. However, Aguilar et al. (2021) did not find an impact on the consumption of food targeted by the tax.

### **6.3 Heterogeneity and potential mechanisms**

This paper focuses on the impact of an SSBs tax on children's health through in-utero exposure, but it is not the only cause of weight gain. Several mitigating factors may explain the heterogeneous effect of the tax on children's outcomes. Children's health outcomes depend on the determinants of the mother's BMI, such as nutrition, level of education, time constraint, physical activity, income, and stress. Some factors are related to the household, such as the number of people in the household living in urban or rural areas, or the level of food insecurity. On the other hand, children's nutritional habits and physical activity also impact their health. This section presents the heterogeneity analysis of the results and the potential mechanisms.

First, the impact SSBs price increase may variate according to the mother's characteristics and environment. The mother's weight is the main channel of interest in the context of in-utero shock. Although I have the BMI of the mother in the database, it is not possible to use the weight of the mother during pregnancy. The maternal BMI variable may be capturing nutritional behavior at the time of the survey and not the pregnancy, which reduces the likelihood that I am observing the in-utero exposure channel. However, it does allow me to observe heterogeneous effects on child outcomes at the time of the survey. I interact the continuous variable of maternal BMI with the tax exposure interaction. Table A3.7 shows that

the intensive effect of tax exposure and the mother's BMI is positively associated with the child's BMI, probability of being overweight, and obesity. On the contrary, table A3.6 shows that the extensive margin of exposure has no significant effect except negatively on the probability of being obese. The interpretation of these results is complex. If possible, these results should be further investigated with a panel database at the time of pregnancy.

The mother's physical activity has likely changed the effect of the tax on health outcomes too. Given the lack of panel data, I observe heterogeneous effects between mothers and not within mothers. Mothers indicated whether they practiced sports in the week before the interview. I interact this discrete variable with the variables of interest in the intensive and extensive models. Tables A3.6 and A3.7 show no significant effect of exposure to price increases relative to physical activity.

Eventually, the mother's time constraint is one of the main drivers of child obesity (Cawley and Liu 2012, Datar et al. 2014, Jabs and Devine 2006). The time constraint describes the lack of time to acquire knowledge, look for, and/or prepare healthy meals. With this database, the time constraint cannot be captured as one of the channels of a child's in-utero exposure. Nevertheless, it may play a role in the purchase decision of SSBs, specifically in certain regions with no healthier and cheaper alternative. Conversely, the tax increases the relative cost of SSBs compared to healthier alternatives. I use mothers' work as a proxy for time constraints. The assumption is that the main time constraint is work. Mothers were asked whether they worked at least one hour in the week before the survey. Unfortunately, there is no variable on the number of work hours. I interact the discrete variable on work status with the interaction term of interest. Table A3.6 shows that children exposed in-utero to price increase and whose mother was working on the previous week are 0.024 kilograms lighter and less likely to be overweight or obese, by 2 percentage points, respectively. The analysis with the extensive margin model finds no significant effect.

Although endogenous, one can also expect a heterogeneous effect of the reform depending on the size of the family: more kids (or larger rank) will be related to more pressure on household resources, and it might be that the high-fertility households do not react as the low-fertility households to the increase in SSB

prices. It might be that they are even more likely to reduce their SSB consumption following the price increase. Table [A3.6](#) shows that children are smaller in larger families. However, the interaction term of interest is not significant for any of the outcomes (tables [A3.6](#) and [A3.7](#)).

Finally, children are also directly exposed to the tax in childhood (between birth and survey years). The database gives information about respondents' nutritional habits. Respondents precise the number of days they drank sodas during the previous week. This variable is available for a sub-sample only for 2012, 2018, and 2020. I test this mechanism using the mother-fixed effects model, as consumption varies from child to child. The new variable of interest is an interaction between the child's SSBs consumption, the exposure to the tax, and the State of birth. Table [A3.8](#) shows that children exposed in-utero to a high price increase who drink more SSB are significantly bigger (weight, BMI, and overweight). Yet, children exposed in-utero to a high price increase are significantly lighter than those not exposed. Results suggest that introducing the tax may not compensate for children's SSB consumption.

## 7 Conclusion

In conclusion, this paper explores the effects of an increase in SSB prices as an in-utero shock. The main outcomes are height, weight, BMI, overweight, and obesity.

The paper exploits geographical price variation to comparing children aged 3-6 years born before and after the tax. The first estimates are similar to the average treatment effect. Although there is a decline in health outcomes, especially for the intensive margin, the results are not significant. However, being born after the implementation of the tax significantly reduces the height. The results are confirmed when maternal fixed effects are introduced to control for unobservable variables, which could impact the mother's and child's nutritional behavior.

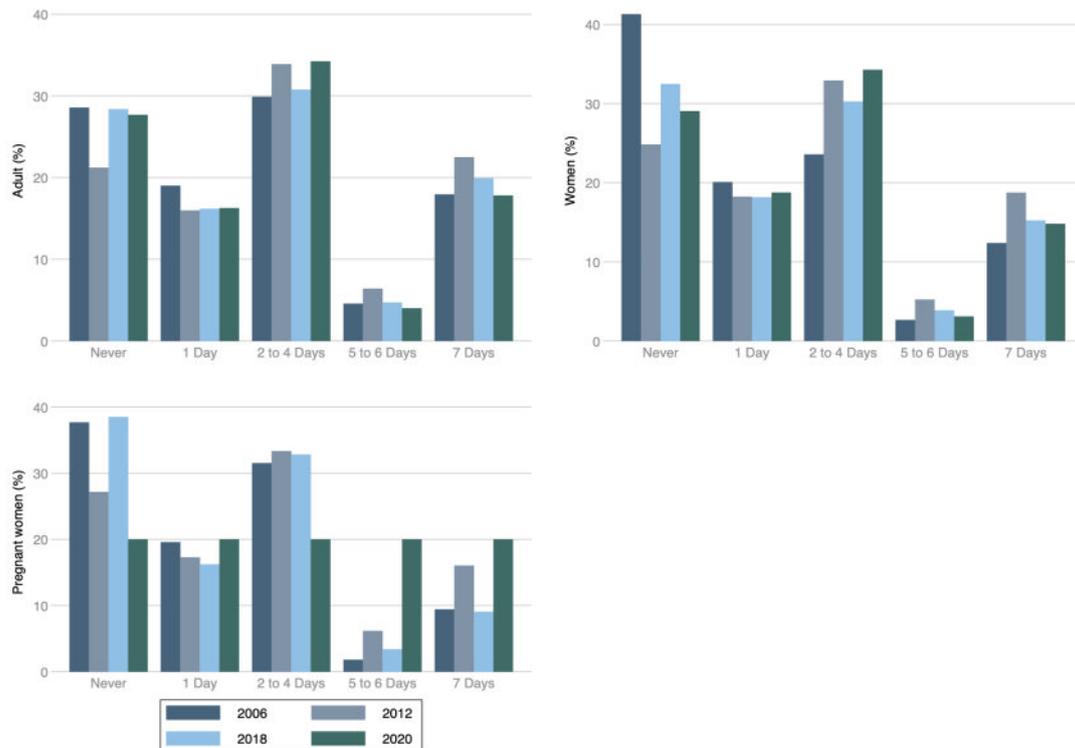
These preliminary results are consistent with the literature as the sin taxes have heterogeneous effects depending on income. Combining its effects with another conditional cash transfer program such as Progresa ([Kronebusch and Damon 2019](#))

would be worthwhile.

It is important to study the impact of this tax on health outcomes as this measure has been threatened by the sodas industry, also thanks to manipulation on the scientific area ([Pedroza-Tobias et al. 2021](#)).

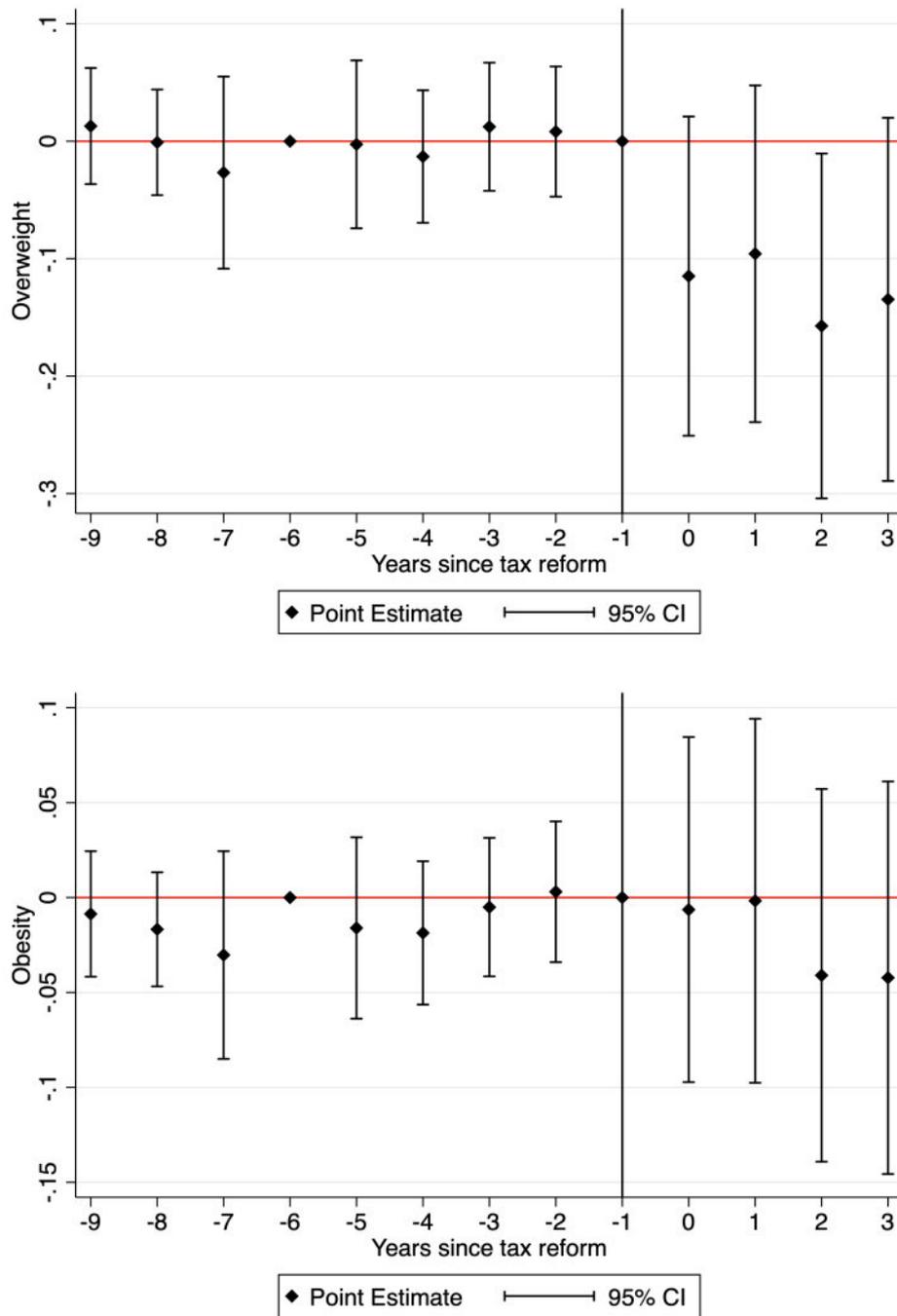
## Appendix A3. Chapter 3

Figure A3.1: SSBs weekly consumption trend (2006-2020)



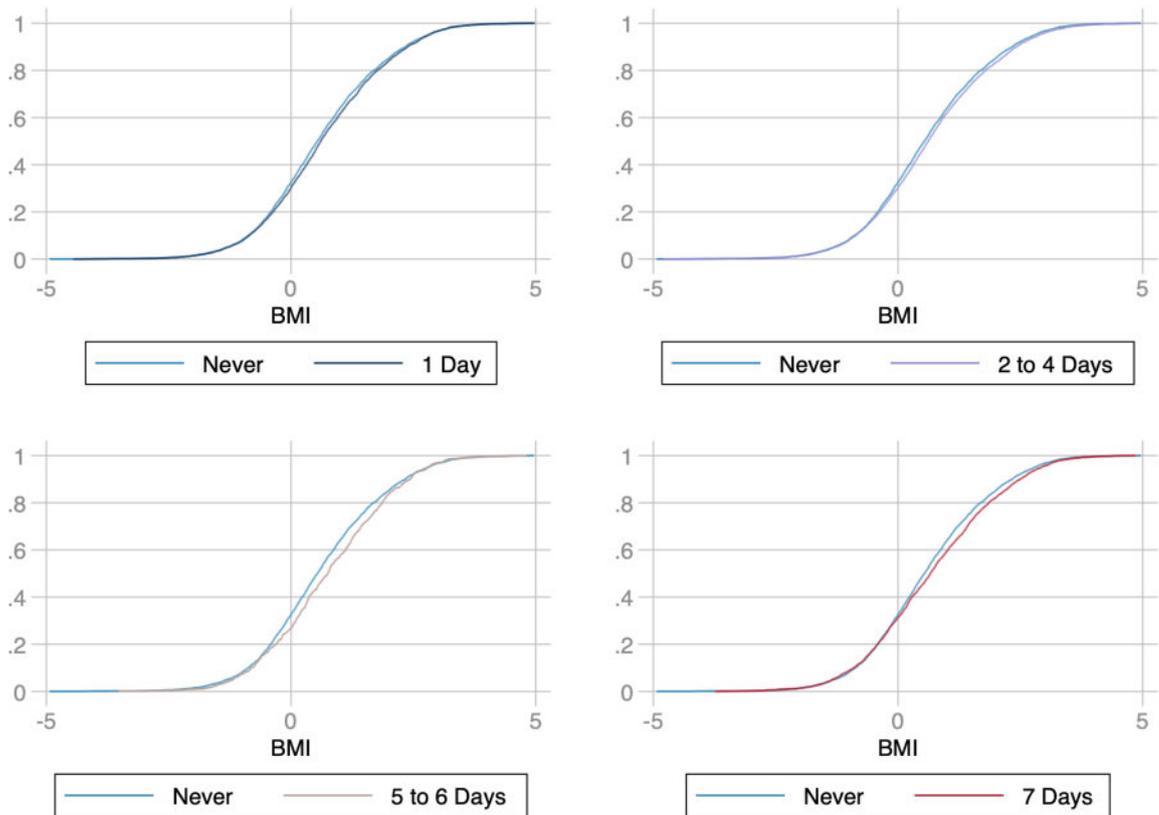
Note: The graph represents the weekly consumption of SSBs in two sub-categories: adults and women and pregnant women. The variable studied is a categorical variable using the answer to the question: "In the last week, how often did you consume soft drinks? This is a self-report measure, obviously subject to the risk of desirability bias. The databases used are 2012, 2018, and 2020. The 2016 survey did not include a questionnaire to harmonize the data. The graph shows a decrease in consumption among adults and women, with an increase in the "Never" response and a decrease in the "7 days" response from 2012 to 2020. The results are less conclusive for the sub-sample of pregnant women, partly because the 2020 database included fewer pregnant women.

Figure A3.2: Children's risk of overweight and obesity



Note: The graph presents the estimates of children's likelihood of overweight and obesity,  $\gamma_j$ , from the equation:  $Y_{i,a} = \alpha + \beta_1 age + \beta_1 Exposure_i + \sum_{j=-9}^3 \gamma_j T_{2014+j} + \beta_3 X'_i + \epsilon_{i,a}$ . The sample includes kids aged 3 to 6. The red line at  $t - 1$  indicates 2013, the year before the tax implementation, which is omitted. The dots represent the fall in overweight but not in obesity. The arrays the upper and lower confidence intervals of the estimates.

Figure A3.3: Correlation obesity and SSBs consumption - children (3 to 6 years old)



Note: The graph represents the cumulative distribution function (CDF) of IMC according to the level of soft drink consumption at the child level. Each graph compares one or more days of consumption to never consumption to show the correlation between the two. The CDF of the IMF of children who consume drinks between 5 and 7 days is smaller than that of children who do not consume beverages, showing higher BMIs for the former.

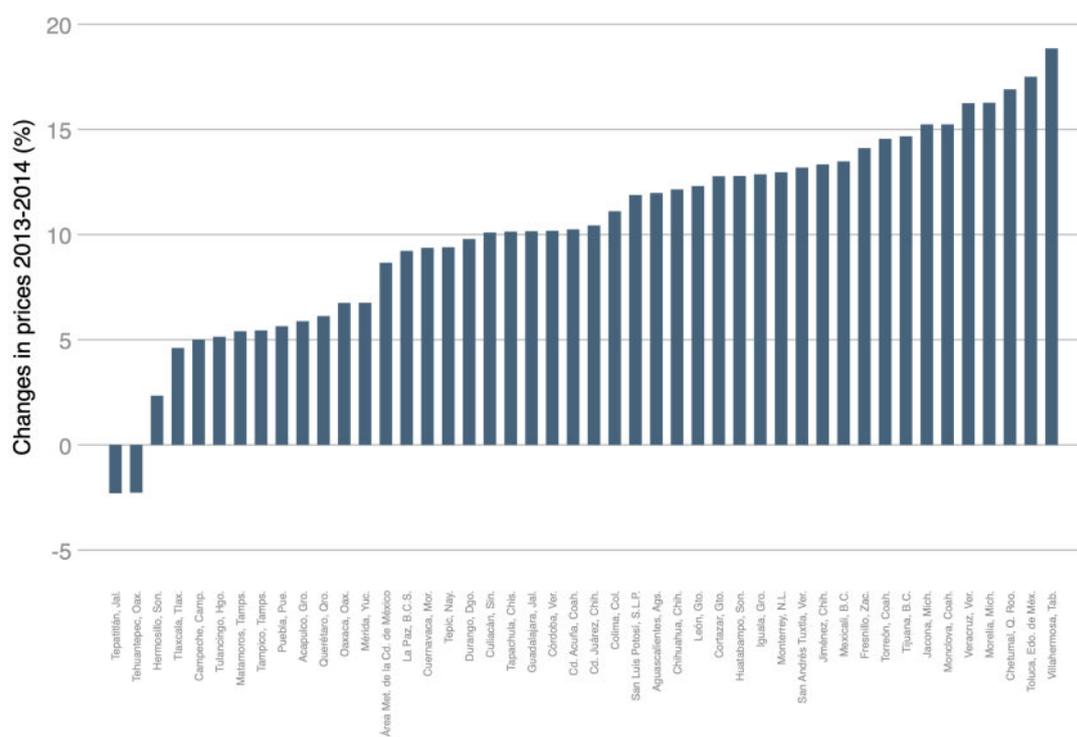
Table A3.1: Summary statistics - child variables

	Pregnancy bf or aft 2014			Obs.	Pregnancy bf & aft 2014			Obs.
	Non Exposed	Exposed	Diff.		Non Exposed	Exposed	Diff.	
Weight (kg)	18.156	16.891	1.265***	3117	20.987	15.556	5.432***	855
Height (cm)	105.674	102.417	3.257***	3117	113.424	98.427	14.997***	855
BMI z-score	0.443	0.342	0.100*	3117	0.493	0.379	0.113	855
Obese	0.044	0.042	0.002	3117	0.075	0.044	0.031*	855
Overweight or obese	0.159	0.120	0.039**	3117	0.203	0.122	0.081***	855
Age	4.515	4.042	0.472***	3117	5.542	3.466	2.076***	855
Gender	1.504	1.504	-0.001	3117	1.476	1.507	-0.031	855
Is currently at school	0.509	0.703	-0.193***	2965	0.975	0.599	0.376***	855
SSB consumption per days in a week	2.429	2.537	-0.109	250	2.478	2.504	-0.026	752
Rural	0.558	0.276	0.281***	3117	0.369	0.381	-0.012	855
Survey 2012	0.858	0.000	0.858***	3117	0.000	0.000	0.000	855
Survey 2016	0.133	0.000	0.133***	3117	0.000	0.000	0.000	855
Survey 2018	0.009	0.323	-0.313***	3117	0.927	0.912	0.015	855
Survey 2020	0.000	0.677	-0.677***	3117	0.073	0.088	-0.015	855

Note: The table reports the sample means of child level variables by control (“Pregnancy bf or aft 2014”) and treatment (“Pregnancy bf & aft 2014”) groups. The sample includes only kids aged 3 to 6 for whom BMI z-score and exposure status are available. The column “Pregnancy bf or aft 2014” gathers siblings born exclusively before (“Non Exposed”) or after (“Exposed”) the SSBs’ price increase. The column “Pregnancy bf & aft 2014” gathers siblings born before (“Non Exposed”) and after (“Exposed”) the SSBs’ price increase. Children “Exposed” are taken after February 28th, 2014, while those “Non Exposed” are born before (see sub-section 4.1 for more details on the date). Column “Diff.” gives the  $t$ -statistics testing if the mean significantly differs between children “Exposed” and “Non Exposed”. BMI z-score is based on raw BMI adjusted to age and gender with the WHO Child Growth Standards and WHO reference 2007 composite datafiles (Vidmar et al. 2013). The result is then converted into percentiles based on a standard normal distribution to capture child-specific anthropometric trends. The risk of being overweight or obese is a discrete variable that equals 1 if the child is in the 75th or 85th largest percentiles, respectively, and 0 otherwise. SSBs consumption gives the number of days of children’s SSBs consumption during the week before the interview. Rural indicates the place of residence during the interview.

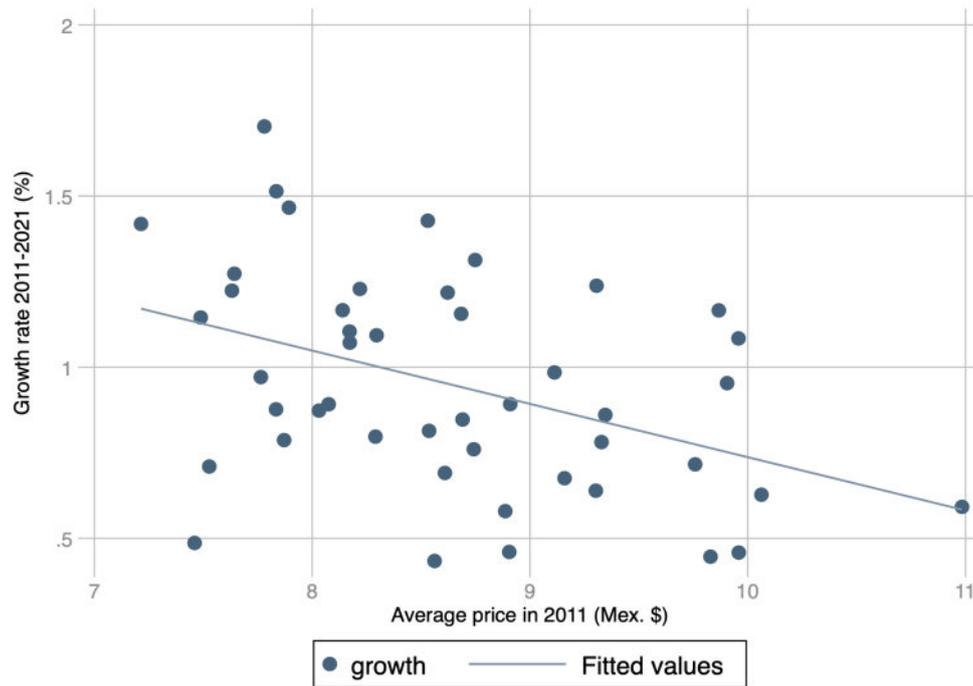


Figure A3.5: SSBs prices changes between 2013 and 2014 - regional level



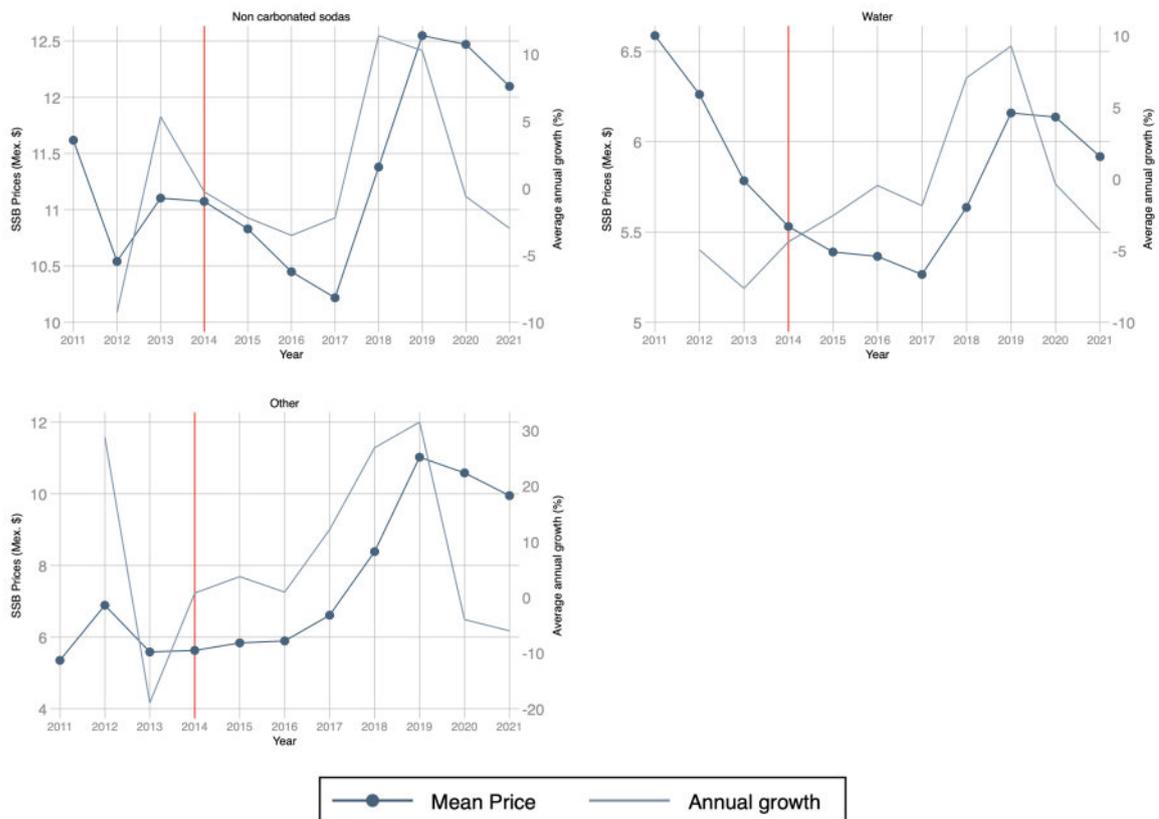
Note: The graph shows the rate of change in real SSBs' prices in 2014 following the implementation of the tax at the regional level. The average annual cost is based on the INEGI database, which gives the nominal prices of beverages sold at retail outlets (e.g., supermarkets, convenience or grocery stores, warehouse clubs, and street stalls) in 46 different cities with more than 20,000 inhabitants each month between 2011 and 2021. All taxes but the value-added taxes are included in the consumer prices. After selecting the carbonated drinks, the nominal price was deflated by the consumer price index specific to beverages, based on December 2011, and averaged at the regional level. The graph shows that the variation ranged from a decrease of about 2.5% to about 18%.

Figure A3.6: SSBs price variation from 2011 to 2021 by price in 2011



Note: The graph plots the regional SSBs prices' growth rate from 2011 to 2021 relative to the regional average prices in 2011. It shows a negative association between the level of prices in 2011 and the price change after the implementation of the tax on SSBs. The sample is restricted to carbonated beverages. INEGI records consumer prices (nominal prices) at retail outlets (e.g., supermarkets, convenience or grocery stores, warehouse clubs, and street stalls) in 46 cities with more than 20,000 inhabitants each month. Prices are deflated using the 2011 Mexican consumer price index for beverages (base December 2011) to obtain the real value and are averaged yearly at the regional levels.

Figure A3.7: Prices variation of other beverages at national level



Note: The graph plots the average annual prices of non-carbonated SSBs, water, and other beverages and their average annual growth rate between 2011 and 2021 at the national level. The average annual price is based on the INEGI database, which gives the nominal prices of beverages sold at retail outlets (e.g., supermarkets, convenience or grocery stores, warehouse clubs, and street stalls) in 46 different cities with more than 20,000 inhabitants each month between 2011 and 2021. All taxes but the value-added taxes are included in the consumer prices. After selecting the carbonated drinks, the nominal price was deflated by the consumer price index specific to beverages, based on December 2011. The final annual average price is not weighted.

Table A3.2: Robustness - Height and Weight z-score

	Height z-score	Weight z-score
	(1)	(2)
<i>Panel A: Intensive margin</i>		
Exposed in-utero (months of pregnancy)	-0.021 (0.027)	0.001 (0.027)
Price increase (annual growth rate)	0.013 (0.140)	0.036 (0.140)
Exposed in-utero x Price increase	-0.001 (0.002)	0.000 (0.002)
Observations	3181	3184
R2	0.088	0.058
Survey's year FE	<i>Yes</i>	<i>Yes</i>
Mother FE	<i>No</i>	<i>No</i>
<i>Panel B: Extensive margin</i>		
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	-0.609*** (0.123)	-0.355*** (0.123)
Price increase (= 1 if annual growth rate > 10%)	0.066 (0.834)	0.028 (0.846)
Exposed in-utero x Price increase	-0.005 (0.090)	-0.075 (0.091)
Obs.	3242	3245
R2	0.030	0.037
Survey's year FE	<i>Yes</i>	<i>Yes</i>
Mother FE	<i>No</i>	<i>No</i>
<i>Panel C: Mother Fixed Effect</i>		
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	-0.610*** (0.131)	-0.404*** (0.121)
Price increase (= 1 if annual growth rate > 10%)	0.644 (0.645)	0.314 (0.591)
Exposed in-utero x Price increase	0.260 (0.161)	0.231 (0.148)
Observations	3745	3750
No. of mothers	2658	2660
R2	0.025	0.016
Survey's year FE	<i>No</i>	<i>No</i>
Mother FE	<i>Yes</i>	<i>Yes</i>

Note: \*\*\* p < .01, \*\* p < .05, \* p < .1 Standard error is in parenthesis. Outcomes for height and weight are replaced by *Height z-score* and *Weight z-score* (see Vidmar et al. (2013) for more details). All regressions control for rural/urban areas, child's school attendance, gender, mother's physical activity, mother marital status, and mother's age. Panel A and B sample includes any child aged 3 to 6, born before or after Jan. 1st, 2014. The sample is restricted to children for whom the BMI z-score is available. The coefficient of interest in Panel A is  $Prices_s^{2013-14} \times Exposure_{i,s}$ . In this sample, *Prices* is the SSBs price growth rate between 2013 and 2014 in the real term. *Exposure* is the number of months of pregnancy after Jan. 1st, 2014. Panel A gives the Average Treatment Effect as an intensive margin. The coefficient of interest in Panel B is  $Prices_s \times Exposure_{i,s}$  where *Price* is a binary variable that equals 1 if the child is born after Feb. 28th, 2014. *Exposure* is a binary variable that equals 1 if child *i* was born in a State where the SSBs prices increased by or by more than 10% in 2013-2014. Panel C sample includes any child aged 3 to 6, born before or after Jan. 1st, 2014. The sample is restricted to children living in households with 2 or more siblings, for whom BMI z-score is available. The regression adds a mother-fixed effects. The coefficient of interest is the interaction between  $Exposed_{in-utero_{i,s,m}}$  and  $Prices_s$  that equals 1 for children born after Feb. 28th, 2014.

Table A3.3: Robustness - Price growth rate

	Height	Weight	BMI	Overweight	Obese
	(1)	(2)	(3)	(4)	(5)
<i>Extensive Margin - 8%</i>					
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	-2.894* ** (0.656)	-0.783* (0.426)	0.119 (0.150)	0.002 (0.032)	0.055 (0.049)
Price increase (= 1 if annual growth rate > 8%)	3.225 (5.370)	0.902 (3.492)	0.069 (1.230)	-0.138 (0.259)	-0.180 (0.401)
Exposed in-utero x Price increase	-0.107 (0.486)	-0.292 (0.316)	-0.131 (0.111)	-0.006 (0.023)	-0.020 (0.036)
Observations	3250	3250	3240	3250	3250
R2	0.665	0.395	0.033	0.023	0.028
Survey's year FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Mother FE	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>
<i>Extensive Margin - 12%</i>					
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	-3.063* ** (0.544)	-0.943* ** (0.354)	0.045 (0.125)	-0.004 (0.026)	0.042 (0.041)
Price increase (= 1 if annual growth rate > 12%)	-2.150 (3.768)	-0.067 (2.451)	0.305 (0.863)	-0.044 (0.182)	-0.010 (0.282)
Exposed in-utero x Price increase	0.157 (0.418)	-0.212 (0.272)	-0.081 (0.096)	0.004 (0.020)	-0.008 (0.031)
Observations	3250	3250	3240	3250	3250
R2	0.665	0.394	0.033	0.023	0.028
Survey's year FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Mother FE	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>
<i>Mother Fixed Effect - 8%</i>					
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	-2.778* ** (0.711)	-0.743* (0.425)	0.092 (0.157)	0.001 (0.034)	0.003 (0.055)
Price increase (= 1 if annual growth rate > 8%)	-2.310 (3.418)	-4.808** (2.031)	-1.458* (0.750)	-0.667* ** (0.164)	-0.343 (0.262)
Exposed in-utero x Price increase	0.805 (0.785)	0.051 (0.468)	-0.072 (0.173)	-0.011 (0.038)	0.015 (0.060)
Observations	3756	3752	3743	3752	3752
No. of mothers	2662	2660	2655	2660	2660
R2	0.863	0.696	0.011	0.029	0.030
Survey's year FE	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>
Mother FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
<i>Mother Fixed Effect - 12%</i>					
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	-2.259* ** (0.511)	-0.823* ** (0.305)	0.021 (0.113)	-0.020 (0.025)	-0.006 (0.039)
Price increase (= 1 if annual growth rate > 12%)	-0.032 (2.431)	1.845 (1.585)	0.279 (0.586)	0.175 (0.128)	-0.035 (0.204)
Exposed in-utero x Price increase	0.165 (0.821)	0.407 (0.489)	0.082 (0.182)	0.051 (0.040)	0.072 (0.063)
Observations	3756	3752	3743	3752	3752
No. of mothers	2662	2660	2655	2660	2660
R2	0.863	0.696	0.007	0.017	0.029
Survey's year FE	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>
Mother FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>

Note: \*\*\* p < .01, \*\* p < .05, \* p < .1 Standard error is in parentheses. The table presents the results of the extensive margin model (model 2) and the mother-fixed effects model (model 3). Two new threshold are used for the price increase: 8% and 12%. The coefficient of interest is the interaction between *Exposedin - utero* and *Prices*. *Exposedin - utero* equals 1 if the child is born after Feb. 28th, 2014 and *Prices* equals 1 if the average growth rate of SSBs price in 2013/2014 is higher than 8% or 12% in the child's state of birth. All regressions control for rural/urban areas, child's school attendance, gender, mother's physical activity, mother marital status, and mother's age.

Table A3.4: Robustness - without Mexico city

	Height	Weight	BMI	Overweight	Obese
	(1)	(2)	(3)	(4)	(5)
<i>Panel A: Intensive margin</i>					
Exposed in-utero (months of pregnancy)	-0.088 (0.130)	0.003 (0.083)	0.025 (0.029)	0.008 (0.010)	0.005 (0.006)
Price increase (annual growth rate)	0.096 (0.650)	0.089 (0.417)	0.037 (0.147)	-0.015 (0.048)	-0.013 (0.030)
Exposed in-utero x Price increase	-0.003 (0.007)	0.004 (0.005)	0.001 (0.002)	0.000 (0.001)	0.000 (0.000)
Observations	3036	3036	3027	3036	3036
R2	0.660	0.395	0.033	0.028	0.025
Survey's year FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Mother FE	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>
<i>Panel B: Extensive margin</i>					
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	-2.931*** (0.614)	-0.720* (0.397)	0.136 (0.141)	0.009 (0.029)	0.079* (0.046)
Price increase (= 1 if annual growth rate > 10%)	0.725 (3.873)	0.138 (2.503)	0.014 (0.884)	-0.110 (0.185)	-0.167 (0.288)
Exposed in-utero x Price increase	-0.088 (0.431)	-0.416 (0.279)	-0.146 (0.099)	-0.019 (0.021)	-0.047 (0.032)
Observations	3097	3097	3088	3097	3097
R2	0.666	0.398	0.034	0.025	0.030
Survey's year FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Mother FE	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>
<i>Panel C: Mother Fixed Effect</i>					
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	-2.887*** (0.616)	-1.119*** (0.367)	0.032 (0.137)	-0.026 (0.030)	-0.009 (0.047)
Price increase (= 1 if annual growth rate > 10%)	3.178 (2.960)	1.390 (1.762)	-0.062 (0.652)	-0.020 (0.143)	0.221 (0.227)
Exposed in-utero x Price increase	1.227 (0.748)	0.766* (0.447)	0.023 (0.166)	0.034 (0.036)	0.043 (0.057)
Observations	3672	3668	3661	3668	3668
No. of mothers	2601	2599	2595	2599	2599
R2	0.863	0.696	0.007	0.014	0.031
Survey's year FE	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>
Mother FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>

Note: \*\*\* p < .01, \*\*p < .05, \* p < .1 Standard error is in parentheses. The table presents the results of the intensive margin model (model 1), the extensive margin model (model 2) and the mother-fixed effects model (model 3). The samples exclude children born in Mexico city to test the robustness of the results. All regressions control for rural/urban areas, child's school attendance, gender, mother's physical activity, mother marital status, and mother's age.

Table A3.5: Robustness - Birth order-fixed effect

	Height	Weight	BMI	Overweight	Obese
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	-3.884 (3.220)	-2.114 (2.113)	-0.195 (0.793)	0.063 (0.175)	-0.105 (0.236)
Price increase (= 1 if annual growth rate > 10%)	3.308 (2.968)	1.505 (1.930)	-0.040 (0.724)	-0.019 (0.160)	0.233 (0.215)
Exposed in-utero x Price increase	1.193 (0.742)	0.674 (0.484)	-0.018 (0.183)	0.027 (0.040)	0.038 (0.054)
Observations	830	827	821	827	827
No. of mothers	569	568	565	568	568
R2	0.886	0.697	0.010	0.033	0.046
Survey's year FE	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>
Mother FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Rank Birth FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>

Note: \*\*\* p < .01, \*\*p < .05, \* p < .1 Standard error is in parentheses. The coefficient of interest is the interaction between *Exposed in - utero* and *Prices*. The coefficient of interest is the interaction between *Exposed in - utero* and *Prices*. *Exposed in - utero* equals 1 if the child is born after Feb. 28th, 2014 and *Prices* equals 1 if the average growth rate of SSBs price in 2013/2014 is higher than 8% or 12% in the child's state of birth. The regression includes birth order and mother-fixed effects. The regression controls for rural/urban areas, child's school attendance, gender, mother's physical activity, mother marital status, and mother's age. The sample includes any child aged 3 to 6, born before or after Jan. 1st, 2014. The sample is restricted to children living in households with 2 or more siblings, for whom BMI z-score is available.

Table A3.6: Heterogeneity - Intensive margin model

	Height	Weight	BMI	Overweight	Obese
	(1)	(2)	(3)	(4)	(5)
<i>Mother's characteristics</i>					
Exposed in-utero (months of pregnancy)	-0.244 (0.441)	0.448 (0.288)	0.180* (0.099)	0.027 (0.022)	0.058* (0.033)
Price increase (annual growth rate)	-1.706 (1.818)	0.489 (1.188)	0.431 (0.407)	0.043 (0.089)	0.106 (0.136)
Exposed in-utero x Price increase	-0.031 (0.039)	-0.068*** (0.025)	-0.017** (0.009)	-0.003 (0.002)	-0.006** (0.003)
Mother's BMI	0.081 (0.056)	0.148*** (0.036)	0.057*** (0.012)	0.006** (0.003)	0.018*** (0.004)
Exposed in-utero x Price increase x Mother's BMI	0.001 (0.001)	0.002*** (0.001)	0.001** (0.000)	0.000 (0.000)	0.000** (0.000)
Observations	2320	2320	2312	2320	2320
R-Square	0.671	0.415	0.104	0.057	0.065
Exposed in-utero (months of pregnancy)	-0.029 (0.143)	0.005 (0.092)	0.017 (0.032)	0.003 (0.007)	0.003 (0.011)
Price increase (annual growth rate)	-2.339 (1.832)	-0.274 (1.183)	0.192 (0.415)	0.019 (0.087)	0.057 (0.135)
Exposed in-utero x Price increase	-0.007 (0.008)	0.002 (0.005)	0.001 (0.002)	0.000 (0.000)	0.000 (0.001)
Mother's sport activity	0.593 (0.652)	0.246 (0.421)	-0.034 (0.148)	-0.004 (0.031)	0.023 (0.048)
Exposed in-utero x Price increase x Mother's sport	0.019 (0.017)	0.004 (0.011)	-0.000 (0.004)	-0.000 (0.001)	-0.001 (0.001)
Observations	3161	3161	3151	3161	3161
R-Square	0.660	0.392	0.032	0.024	0.027
Exposed in-utero (months of pregnancy)	-0.138 (0.155)	-0.105 (0.100)	-0.009 (0.035)	-0.006 (0.007)	-0.005 (0.011)
Price increase (annual growth rate)	-2.610 (1.836)	-0.392 (1.184)	0.200 (0.416)	0.018 (0.087)	0.050 (0.135)
Months x Price increase	0.003 (0.009)	0.011* (0.006)	0.003 (0.002)	0.001* (0.000)	0.001 (0.001)
Mother's work	0.206 (0.586)	0.107 (0.378)	0.012 (0.133)	-0.020 (0.028)	0.032 (0.043)
Exposed in-utero x Price increase x Mother's work	-0.019 (0.015)	-0.024** (0.010)	-0.005 (0.003)	-0.002*** (0.001)	-0.002* (0.001)
Observations	3161	3161	3151	3161	3161
R-Square	0.659	0.393	0.033	0.026	0.028
<i>Household's characteristics'</i>					
Exposed in-utero (months of pregnancy)	-0.284 (0.276)	-0.022 (0.178)	0.058 (0.063)	0.001 (0.013)	0.020 (0.020)
Price increase (annual growth rate)	-2.834 (1.831)	-0.553 (1.181)	0.161 (0.416)	0.009 (0.087)	0.047 (0.135)
Exposed in-utero x Price increase	0.029 (0.022)	0.023 (0.014)	0.002 (0.005)	0.001 (0.001)	0.000 (0.002)
Family size	-0.537*** (0.152)	-0.137 (0.098)	0.029 (0.034)	-0.002 (0.007)	0.009 (0.011)
Exposed in-utero x Price increase x Family size	-0.007 (0.005)	-0.005 (0.003)	-0.000 (0.001)	-0.000 (0.000)	0.000 (0.000)
Observations	3161	3161	3151	3161	3161
R-Square	0.661	0.397	0.035	0.025	0.031
Exposed in-utero (months of pregnancy)	-0.284 (0.276)	-0.022 (0.178)	0.058 (0.063)	0.001 (0.013)	0.020 (0.020)
Price increase (annual growth rate)	-2.834 (1.831)	-0.553 (1.181)	0.161 (0.416)	0.009 (0.087)	0.047 (0.135)
Exposed in-utero x Price increase	0.029 (0.022)	0.023 (0.014)	0.002 (0.005)	0.001 (0.001)	0.000 (0.002)
Family size	-0.537*** (0.152)	-0.137 (0.098)	0.029 (0.034)	-0.002 (0.007)	0.009 (0.011)
Exposed in-utero x Price increase x Family size	-0.007 (0.005)	-0.005 (0.003)	-0.000 (0.001)	-0.000 (0.000)	0.000 (0.000)
Observations	3161	3161	3151	3161	3161
R-Square	0.661	0.397	0.035	0.025	0.031

Note: \*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .1$  Standard error is in parentheses. The table presents the results of heterogeneity analysis relative to mother's and household's characteristics. This table displays results of the intensive margin models. The interaction term of interest  $Price\ increase_s \times Exposed\ in-utero_{i,s,m}$  is interacted with mother's BMI, mother's sport activity, mother's work and family size. All regressions control for rural/urban areas, child's school attendance, gender, mother's physical activity, mother marital status, and mother's age.

Table A3.7: Heterogeneity - Extensive margin model

	Height	Weight	BMI	Overweight	Obese
	(1)	(2)	(3)	(4)	(5)
<i>Mother's characteristics</i>					
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	-0.419 (2.014)	0.203 (1.324)	0.529 (0.458)	0.049 (0.099)	0.115 (0.151)
Price increase (= 1 if annual growth rate > 10%)	1.480 (2.124)	-2.459* (1.397)	-1.396*** (0.480)	-0.114 (0.105)	-0.232 (0.159)
Exposed x Price increase	0.569 (2.467)	1.751 (1.623)	0.125 (0.560)	0.080 (0.122)	0.233 (0.185)
Mother's BMI	0.073** (0.033)	0.144*** (0.022)	0.057*** (0.007)	0.008*** (0.002)	0.014*** (0.002)
Exposed x Price increase x Mother's BMI	-0.033 (0.084)	-0.080 (0.055)	-0.010 (0.019)	-0.004 (0.004)	-0.011* (0.006)
Observations	2335	2335	2327	2335	2335
R-Square	0.675	0.419	0.105	0.059	0.070
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	-3.156*** (0.610)	-0.898** (0.397)	0.048 (0.140)	-0.005 (0.029)	0.051 (0.046)
Price increase (= 1 if annual growth rate > 10%)	3.564*** (0.861)	1.174** (0.560)	-0.219 (0.197)	0.017 (0.041)	-0.015 (0.064)
Exposed x Price increase	0.101 (0.468)	-0.269 (0.304)	-0.072 (0.107)	-0.003 (0.022)	-0.031 (0.035)
Mother's sport activity	-0.021 (0.425)	-0.017 (0.276)	-0.063 (0.097)	0.006 (0.020)	-0.003 (0.032)
Exposed x Price increase x Mother's sport	-0.436 (0.932)	-0.351 (0.606)	-0.241 (0.214)	-0.050 (0.045)	-0.055 (0.070)
Observations	3221	3221	3211	3221	3221
R-Square	0.664	0.395	0.033	0.025	0.029
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	-3.336*** (0.640)	-1.031** (0.416)	0.003 (0.147)	0.001 (0.031)	0.042 (0.048)
Price increase (= 1 if annual growth rate > 10%)	3.428*** (0.871)	1.166** (0.566)	-0.184 (0.199)	0.022 (0.042)	-0.010 (0.065)
Exposed x Price increase	-0.034 (0.520)	-0.445 (0.338)	-0.122 (0.119)	-0.038 (0.025)	-0.056 (0.039)
Mother's work	0.086 (0.389)	-0.015 (0.253)	-0.001 (0.089)	-0.009 (0.019)	0.018 (0.029)
Exposed x Price increase x Mother's work	0.067 (0.820)	0.276 (0.533)	0.016 (0.188)	0.060 (0.039)	0.038 (0.061)
Observations	3221	3221	3211	3221	3221
R-Square	0.664	0.395	0.034	0.026	0.030
<i>Household's characteristics</i>					
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	-5.110*** (1.028)	-1.464** (0.669)	0.202 (0.237)	-0.047 (0.050)	0.086 (0.077)
Price increase (= 1 if annual growth rate > 10%)	2.658** (1.120)	1.341* (0.729)	0.004 (0.257)	0.017 (0.054)	0.083 (0.084)
Exposed x Price increase	0.712 (1.196)	-0.368 (0.778)	-0.343 (0.275)	0.041 (0.058)	-0.132 (0.089)
Family size	-0.483*** (0.115)	-0.185** (0.075)	0.000 (0.026)	-0.006 (0.006)	-0.003 (0.009)
Exposed x Price increase x Family size	-0.160 (0.228)	0.004 (0.148)	0.045 (0.052)	-0.011 (0.011)	0.019 (0.017)
Observations	3221	3221	3211	3221	3221
R-Square	0.667	0.398	0.034	0.025	0.032
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	-5.110*** (1.028)	-1.464** (0.669)	0.202 (0.237)	-0.047 (0.050)	0.086 (0.077)
SSB Price increase >10%=1	2.658** (1.120)	1.341* (0.729)	0.004 (0.257)	0.017 (0.054)	0.083 (0.084)
Born after Jan 1st, 2014=1 x SSB Price increase >10%=1	0.712 (1.196)	-0.368 (0.778)	-0.343 (0.275)	0.041 (0.058)	-0.132 (0.089)
Family size	-0.483*** (0.115)	-0.185** (0.075)	0.000 (0.026)	-0.006 (0.006)	-0.003 (0.009)
Born after Jan 1st, 2014=1 x SSB Price increase >10%=1 x Family size	-0.160 (0.228)	0.004 (0.148)	0.045 (0.052)	-0.011 (0.011)	0.019 (0.017)
Observations	3221	3221	3211	3221	3221
R-Square	0.667	0.398	0.034	0.025	0.032

Note: \*\*\* p < .01, \*\*p < .05, \* p < .1 Standard error is in parentheses. The table presents the results of heterogeneity analysis relative to mother's and household's characteristics. This table displays results of the intensive margin models. The interaction term of interest  $Price\ increase_s \times Exposed\ in\ utero_{i,s,m}$  is interacted with mother's BMI, mother's sport activity, mother's work and family size. All regressions control for rural/urban areas, child's school attendance, gender, mother's physical activity, mother marital status, and mother's age.

Table A3.8: Mechanism - Children's characteristics

	Height	Weight	BMI	Overweight	Obese
	(1)	(2)	(3)	(4)	(5)
<i>SSB consumption</i>					
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	1.052 (1.811)	0.882 (1.189)	0.186 (0.465)	0.086 (0.105)	0.058 (0.144)
Price increase (= 1 if annual growth rate > 10%)	6.034 (4.308)	6.064** (2.829)	1.844* (1.093)	0.352 (0.249)	0.258 (0.342)
Exposed in-utero x Price increase	-0.740 (1.820)	-2.523** (1.199)	-1.004** (0.468)	-0.222** (0.106)	-0.069 (0.145)
Child's SSB consumption	0.280 (0.685)	0.759* (0.450)	0.249 (0.174)	0.088** (0.040)	0.062 (0.054)
Exposed in-utero x Price increase x SSB consumption	0.911 (0.679)	1.276* * * (0.447)	0.350** (0.174)	0.097** (0.039)	0.032 (0.054)
Observations	951	948	941	948	948
No. of mothers	723	721	717	721	721
R2	0.890	0.705	0.059	0.070	0.050
Mother FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
<i>Being a migrant</i>					
Exposed in-utero (= 1 if born aft Feb. 28, 2014)	-2.183** (0.848)	-0.757 (0.516)	0.179 (0.199)	0.001 (0.042)	0.051 (0.061)
Price increase (= 1 if annual growth rate > 10%)	3.152 (3.085)	1.410 (1.874)	-0.060 (0.717)	-0.019 (0.153)	0.220 (0.221)
Exposed in-utero x Price increase	1.198 (0.772)	0.684 (0.471)	-0.009 (0.181)	0.029 (0.038)	0.036 (0.056)
Born abroad	4.936 (8.689)	1.814 (5.277)	0.406 (2.019)	-0.062 (0.430)	-0.153 (0.623)
Exposed in-utero x Price increase x Born abroad	3.329 (8.698)	1.144 (5.283)	0.007 (2.021)	-0.068 (0.430)	-0.093 (0.623)
Observations	1290	1286	1278	1286	1286
No. of mothers	925	923	919	923	923
R2	0.864	0.687	0.009	0.026	0.050
Mother FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>

Note: \*\*\* p <.01, \*\*p <.05, \* p <.1 Standard error is in parentheses. All regressions includes mother-fixed effects and control for rural/urban areas, child's school attendance, gender and age. The sample includes any child aged 3 to 6, born before or after Jan. 1st, 2014. The top part of the table - SSB consumption - presents the estimates of the following regression  $Y_{i,s,a,m} = \alpha + \beta_1(Price\ increase_s \times Exposed\ in-utero_{i,s,m} \times SSBs\ consumption_i) + \beta_2 Price\ increase_s + \beta_3 Exposed\ in-utero_{i,s,m} + \beta_4 SSBs\ consumption_i + \beta_5 X'_{i,s,m} + \delta_m + \delta_s + \epsilon_{i,s,m}$ . The bottom part of the table - Being a migrant - presents the estimates of the following regression  $Y_{i,s,a,m} = \alpha + \beta_1(Price\ increase_s \times Exposed\ in-utero_{i,s,m} \times Born\ abroad_i) + \beta_2 Price\ increase_s + \beta_3 Exposed\ in-utero_{i,s,m} + \beta_4 Born\ abroad_i + \beta_5 X'_{i,s,m} + \delta_m + \delta_s + \epsilon_{i,s,m}$ .

## Chapter 4

# Predicting Covid-19's spread in Africa: rural and relatively young population may limit the spread and severity

*This chapter was co-authored with Binta Zahra Diop (University of Oxford), Marième Ngom (Argonne National Laboratory) and John N. Poug   Biyong (University of Oxford).*

### **Abstract**

A novel coronavirus disease 2019 (COVID-19) has spread to all regions of the world. There is great uncertainty regarding how countries' characteristics will affect the spread of the epidemic; to date, there are few studies that attempt to predict the spread of the epidemic in African countries. In this paper, we investigate the role of demographic patterns, urbanisation and comorbidities on the possible trajectories of COVID-19 in Ghana, Kenya and Senegal. Methods We use an augmented deterministic Susceptible-Infected-Recovered model to predict the true spread of the disease, under the containment measures taken so far. We disaggregate the infected compartment into asymptomatic, mildly symptomatic and severely symptomatic to match observed clinical development of COVID-19. We also account for age structures, urbanisation and comorbidities (HIV, tuberculosis, anaemia). In our baseline model, we project that the peak of active cases will occur in July, subject to the effectiveness of policy measures. When accounting for the urbanisation, and factoring in comorbidities, the peak may occur between 2 June and 17 June (Ghana), 22 July and 29 August (Kenya) and, finally, 28 May and 15

June (Senegal). Successful containment policies could lead to lower rates of severe infections. While most cases will be mild, we project in the absence of policies further containing the spread, that between 0.78% and 1.03%, 0.61% and 1.22%, and 0.60% and 0.84% of individuals in Ghana, Kenya and Senegal, respectively, may develop severe symptoms at the time of the peak of the epidemic. Compared with Europe, Africa's younger and rural population may modify the severity of the epidemic. The large youth population may lead to more infections but most of these infections will be asymptomatic or mild, and will probably go undetected. The higher prevalence of underlying conditions must be considered.

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## Summary

### What is known?

- While most COVID-19 studies focus on western and Asian countries, very few are concerned with the spread of the virus in African countries.
- Most African countries have relatively low urbanization rates, a young population and context-specific co-morbidities that are still to be explored in the spread of COVID-19.

### What are the new findings?

- In our baseline predictions 33 to 50% of the public will be actively infected at the peak of the epidemic and 1 in 36 (Ghana), 1 in 40 (Kenya) and 1 in 42 (Senegal) of these active cases may be severe.
- With rural areas, infection may be lowered to 65-73% (Ghana), 48-71% (Kenya) and 61-69% (Senegal) of the baseline infections.
- Comorbidities may however increase the ratio of severe infections among the active cases at the peak of the epidemic.

### What do the new findings imply?

- Rural areas and large youth population may limit the spread and severity of the epidemic and outweigh the negative impact of HIV, tuberculosis and anemia.

## 1 Introduction

Since the first reported severe acute syndrome coronavirus 2 (SARS-CoV-2) infection in December 2019, the virus has spread to all continents ([Johns Hopkins Coronavirus Resource Center 2020](#)). There is still little evidence on the pattern of the spread in Africa. Although the African continent is made up of countries with different infrastructures, health policies, and characteristics in the face of this novel coronavirus disease 2019 (COVID-19); some characteristics such as a young population ([Uneca 2020](#)), co-morbidities (tuberculosis, HIV, anemia, [Lancet \(2020\)](#), [Bcheraoui et al. \(2020\)](#), [Worldometer \(2020b\)](#)) and finally low urbanization rates transcend these differences and have been seldom considered in the large number of studies published to date. For example, the median age below 20, ([Worldometer 2020a](#)) and the low rates of urbanization, could potentially lead to a lower death toll of the epidemic in African countries than elsewhere. However, having a young population implies that many infected individuals may not display symptoms and will risk infecting more people than would symptomatic individuals. ([Lee et al. 2020](#)) Additionally, the large number of informal settlements could accentuate this phenomenon. It is therefore urgent to develop a framework that could accurately predict the spread of the virus, accounting for the idiosyncrasies of the African context. A country-specific model will provide policy makers with a wide range of prediction scenarios, based on different actions they can take to address the pandemic. With the scarce resources at their disposal ([The Economist 2020](#), [Barasa et al. 2020](#)), models like these will help target prevention strategies to individuals with co-morbidities who might suffer the most from the epidemic. Moreover, with containment policies that can grind economies to a halt ([Organisation for Economic Co- operation and Development \(OECD\) 2020](#)), understanding the trade-off between rural and urban spreads could lead to better informed decisions between the short term impacts of the epidemic, and the long-term looming shortage in the food-supply that could stem enforcing strict social distancing measures in rural areas.

This study contributes to the meager literature on the burden of the virus on African countries; it also adds to the use of differential equation models to

predict the spread of epidemics. This paper focuses on three African countries that have received little attention: Ghana, Kenya, and Senegal. We chose Kenya to have a comparison point with another in-depth study by [Brand et al. \(2020\)](#) Ghana and Senegal on the other hand have had transparent data sharing policies from the start of the epidemic; they made available publicly the number of positive cases, the number tests conducted and a clear outline of the containment measures. Ghana has an extensive testing policy, while Senegal has tested very few individuals comparatively<sup>1</sup>, we are thus able to see the difference in predictions for two countries that have adopted widely different testing strategies.

To project the trends of the epidemic, we augment the canonical *Susceptible - Infected - Recovered* by splitting the infected compartment into three groups: an infected without symptoms, an infected with mild symptoms, and finally, the infected with severe symptoms. With our projections accounting for policies implemented to date, we present different scenarios accounting for local policies, urbanization, and co-morbidities. Our strategy is relevant beyond the application of this paper; it could be used in Asian or European contexts as well, and is similar to work by [Ferguson et al. \(2020\)](#) who discuss suppression and mitigation measures in the UK and the USA.

## 2 Methods

### 2.1 Compartmental epidemiological model

Several models have been used to predict the spread of the virus. [Read et al. \(2020\)](#) use a standard *Susceptible - Exposed - Infected - Recovered* (SEIR) model with an exposed compartment that comprises infected individuals who do not yet have symptoms and who are not infectious. [Danon et al. \(2020\)](#) also use a SEIR model but split the infected compartment into two sub-compartments: mild symptoms and symptomatic. Finally, [Arenas et al. \(2020\)](#) study use a model composed of *susceptible, exposed, asymptomatic infectious, infected, hospitalized to ICU, dead, and recovered* compartments; however, they assume that all asymptomatic

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<sup>1</sup>As of May 1st, 2020, Ghana has conducted 3.37 tests per thousand individuals while Kenya and Senegal are respectively at 0.4 and 0.76. ([Worldometer 2020a](#))

infectious individuals cannot recover before they ever develop symptoms.

There is early evidence that a large number of individuals infected with COVID-19 will recover without ever developing symptoms and that asymptomatic individuals are contagious to varying degrees (Mizumoto et al. 2020, Nishiura et al. 2020, Ganyani et al. 2020, Al-Tawfiq 2020). Based on these findings, our model assumes that individuals are contagious from the moment they get infected. We define a *Susceptible - Infected - Recovered* (SIR) model with vital dynamics (see figure 1 of the appendix). The known natural progression of the disease is (1) asymptomatic, (2) mild symptomatic, (3) moderate symptomatic, (4) severe, and (5) critical. There are benefits in understanding the heterogeneity among infected individuals namely, those carriers without symptoms (asymptomatic), carriers without symptoms (mild and moderately symptomatic), and severe cases who might seek medical attention (severe and critical). We therefore propose to divide the *infected* compartment into three sub-compartments: asymptomatic infectious, mildly (and moderate) symptomatic infectious, and severely (and critically) infected requiring medical attention.

We introduce some notations.  $S$  is the share of susceptible, i.e. individuals who are exposed to the virus but not immune.  $I_{as}$ ,  $I_{ms}$ , and  $I_{ss}$  are respectively the shares of asymptomatic, mildly symptomatic, and severely symptomatic individuals.  $R$  is the share of immune individuals.  $D$  is the share of deceased individuals (due to COVID-19 and other non-related causes). All numbers are expressed in terms of percentages of the total population. We note  $I = I_{as} + I_{ms} + I_{ss}$  the total share of infected and  $N = S + I + R$  the share of individuals alive. We suppose that borders are closed. Moreover, all compartments experience natural vital dynamics via the birth rate  $\mu_{birth}$  and the death rate  $\mu_{death}$  from causes unrelated to the virus (e.g. long-term diseases, accidents). Daily epidemic transmission is described by equations (4.1)-(4.5):

$$\frac{dS}{dt} = -\beta SI + \mu_{birth}(S + R) - \mu_{death}S \quad (4.1)$$

where  $\beta SI = \beta_{as}SI_{as} + \beta_{ms}SI_{ms} + \beta_{ss}SI_{ss}$

$\beta_{as}$  is the contact rate between asymptomatic *infected* individuals and *susceptible* ones. Because asymptomatic individuals are not aware of their infection, their rate

of contact with susceptible individuals is the same as the rate of contact within the group of *susceptible* individuals. This contact rate will vary with containment measures that are enforced within each country. We define the asymptomatic effective reproduction number  $R_t = \beta_{as}T_{rec,as}$  as the average number of secondary cases per asymptomatic case at time  $t$ .

$\beta_{ms}$  is the contact rate between mildly symptomatic individuals and susceptible ones. It is assumed to be lower than  $\beta_{as}$  because symptomatic individuals tend to self-isolate, either because they are bedridden due to their symptoms or simply because they want to limit contacts with *susceptible* individuals.

$\beta_{ss}$  is the contact rate between severely symptomatic and *susceptible* individuals. Individuals who experience severe symptoms may seek medical care and get admitted as inpatients at a hospital. They might not get hospital care for various reasons (e.g. health facilities are overwhelmed). This rate accounts for contacts between hospitalized patients and healthcare workers, but can also be interpreted as contacts between severely symptomatic individuals and any care-giver (at home for instance, if the health services are overloaded). It also accounts for the contacts between hospitalized severely symptomatic individuals and *susceptible* individuals outside of their care-takers. It remains unclear how contacts other than healthcare workers affect the value of  $\beta_{ss}$ .

$$\frac{dI_{as}}{dt} = \beta SI - \frac{r_{as}}{T_{rec,as}}I_{as} - \frac{(1-r_{as})}{T_{inc}}I_{as} - \mu_{death}I_{as} \quad (4.2)$$

where  $r_{as}$  is the probability of recovery without ever developing symptoms,  $T_{rec,as}$  is the recovery time of an asymptomatic individual, and  $T_{inc}$  is the incubation period during which an individual is infected and infectious, but does not have symptoms.

$$\frac{dI_{ms}}{dt} = \frac{(1-r_{as})}{T_{inc}}I_{as} - \frac{d_{ms}}{T_f}I_{ms} - (1-d_{ms})\left(\frac{r_{ms}}{T_{rec,ms}} + \frac{1-r_{ms}}{T_{sev}}\right)I_{ms} - \mu_{death}I_{ms} \quad (4.3)$$

where  $d_{ms}$  is the probability of dying from a fast deterioration,  $T_d$  is the time elapsed between the appearance of first symptoms and the death of the individual,  $r_{ms}$  is the probability to recover from mild symptoms,  $T_{rec,ms}$  is the recovery time

associated with  $r_{ms}$  and  $T_{sev}$  is the time for severe symptoms to develop. We deviate for the recovery rates of the mildly symptomatic compartment  $r_{ms}$  by taking the weighted average of age-grouped fatality rates of COVID-19 found in Hubei, Hong Kong, and Macau (Oliver et al. 2020):

$$r_{ms} = \sum_{ag} w_{ag}(1 - f_{ag})$$

Where the sum is over the age groups  $ag \in \{[0, 9], [10, 19], \dots, [70, 79], 80+\}$ ,  $w_{ag}$  is the share of the population in age group  $ag$  and  $f_{ag}$  is the fatality rate found in earlier studies for the population in age group (Ganyani et al. 2020).

$$\frac{dI_{ss}}{dt} = \frac{(1 - r_{ms})(1 - d_{ms})}{T_{sev}} I_{ms} - \frac{d_{ss}}{\alpha T_f} I_{ss} - \frac{(1 - d_{ss})}{T_{rec,ss}} I_{ss} - \mu_{death} I_{ss} \quad (4.4)$$

Where  $d_{ss}$  is the probability of dying after progressively developing severe symptoms that require hospitalization,  $T_{rec,ss}$  is the recovery time of the severely symptomatic.  $\alpha T_d$  is the time to death from the start of severe symptoms, for individuals who pass away from severe, progressively developing symptoms. Intuitively, if most severe cases are hospitalized,  $\alpha$  should be higher than 1 as health professionals will slow down the evolution of the disease.

$$\frac{dR}{dt} = r_{vacc} S + \frac{r_{as}}{T_{rec,as}} I_{as} + (1 - d_{ms}) \frac{r_{ms}}{T_{rec,ms}} I_{ms} + \frac{(1 - d_{ss})}{T_{rec,ss}} I_{ss} - (\mu_{imm} + \mu_{death}) R \quad (4.5)$$

$$\frac{dD}{dt} = \mu_{death} N + \frac{\delta_{ms} T_d}{I_{ms}} + \frac{\delta_{ss}}{\alpha y_d} I_{ss} \quad (4.6)$$

In our simulations, we include fatalities, but we do not include the outcomes in the results. We make this choice because of the high uncertainty around the capacity of the healthcare systems of each individual country to absorb the increased demand from severely ill patients. For instance, with the same predictions, a country that has a stock of ventilators of 1,000 will likely have less fatalities than a country with no ventilators. Because we do not have data on healthcare capacities, therefore we chose not to present these results. Our predicted number

of fatalities are however subtracted from the number of susceptibles.

## 3 Results

### 3.1 Baseline Simulations

We use publicly available data from the European Center for Disease Control and Prevention, and from daily press releases made by the Senegalese ministry of health and social protection (Ganyani et al. 2020, Roser and Ritchie 2020a). We also do checks using the Ghana Health Service and the Kenya ministry of health websites.

Whenever possible, we use values of parameters drawn from the literature to fit the model (see table 1).

Although there are reports that as many as 80% of active cases are asymptomatic (Day 2020), these reports are based on cases that are still active but with patients who might go on to develop symptoms. We thus use 40% as the share of individuals infected with COVID-19 who recover without ever developing symptoms (Mizumoto et al. 2020, Nishiura et al. 2020, Ganyani et al. 2020, Al-Tawfiq 2020).

Ghana, Kenya, and Senegal have extensive communication strategies including in local languages to ensure that communities are able to detect the symptoms of COVID-19 such as a cough and fever and would report any person with those symptoms. We there use the share of individuals who do not have a cough as a proxy for the rate of symptomatic infected individuals who can leave their home without being reported. Wang et al. (2020) find that 59% of individuals who test positive for COVID-19 have a cough which implies  $\beta_{ms} = 0.41\beta_{as}$ . We set  $\beta_{ss} = \beta_{as}/T_{rec,ss}$  because we presume that individuals would be most at risk of infecting other susceptible individuals during their transport to the hospital and so this ratio that a severely ill patient would infect as many individuals over the course of their being in the severely symptomatic sub-compartment as an asymptomatic but infectious patient would in one day.

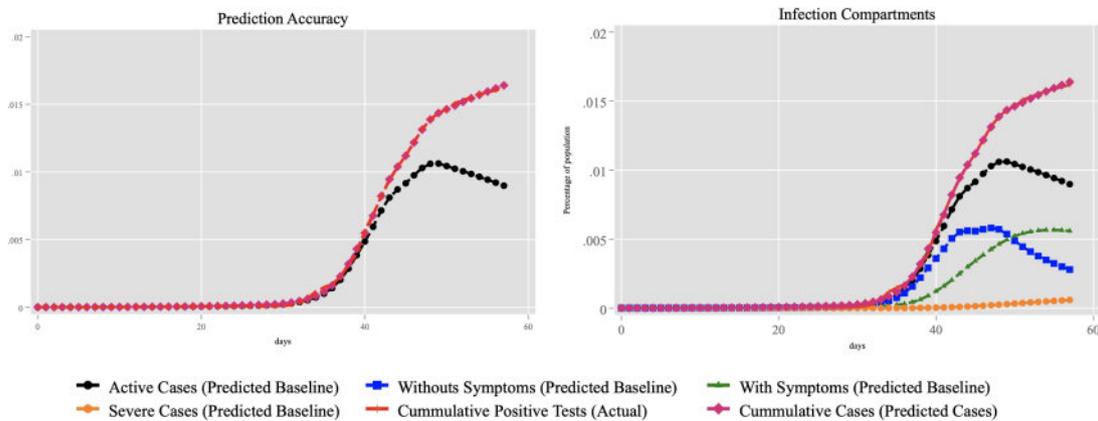
We chose South-Korea as a benchmark to validate  $\beta_{ms}$ ,  $\beta_{ss}$ , and other parameters of our model because it is cited as an example for its extensive testing, tracking, and tracing of infections. We calibrate  $R_t$  by allowing it to change at each new containment measure taken by South-Korean authorities until the number of identified cases reach a plateau. We solve an optimization problem constrained by (4.1)-(4.5) using the MATLAB optimization codes of D’Errico (2020). The values of  $R_t$  obtained and other parameters are summarized in table 1. The number of infections computed with our model accurately approximates the positive cases in South-Korea (see figure 4.1).

For the fatality rates  $d_{ss}$  and  $d_{ms}$  in Ghana, Kenya and Senegal, we split the reported regional fatality rate 2.37% between  $d_{ss} = 2\%$  and  $d_{ms}=0.37\%$  as most deaths occurred for the severely symptomatic (Africa CDC 2020). However, in South Korea, we use the South Korean COVID-19 fatality rate — 1.07% as of April 2, 2020 — and split it across  $d_{ms}=0.03\%$  and  $d_{ss}=1.04\%$ .

$I_{ms}$  was initialized with the number of cases tested positive on the first day of the epidemic in the country.

$I_{as}$  was initialized with the number of cases  $T_{inc} = 5$  days after this same date.  $I_{ss}$  was initialized at 0.

Figure 4.1: Benchmark, South Korea



For Ghana and Senegal,  $R_t$  is tuned to match the number of official cases until the first reported case of community transmission (see table 1), that is the

transmission that cannot be traced back to one of the initial cases. Then,  $R_t$  is increased once and then lowered as soon as the first containment policy is enacted in the country and further lowered at each additional containment measure. Because Kenya first reported community transmission case coincided with the enforcement of a curfew to limit the spread of the virus, we only change  $R_t$  once for both the community transmission and the curfew.

Since they alter  $R_t$ , our baseline projections account for mitigation policies that were put in place in each of these countries (see figure 2). For instance, on the eighth day of the epidemic, Ghanaian officials restricted internal travels between infectious hot-spots and the rest of the country. Because these restrictions were announced 48 hours before they were effective, there is anecdotal evidence that a lot of individuals who lived in these hotspots travelled to other areas of the countries; we thus increase  $R_t$  for two days, before decreasing it again when the internal limitations of travel were effective. Similarly,  $R_t$  is tailored to each of the three countries according to the different policies they enforced. For example, in Kenya, we decrease it less for school closings than for regional lockdowns.

At the date of each containment measure, we adjust the value of  $R_t$  and provide low policy and high policy effectiveness scenarios. Our baseline projections assume a moderate impact of the policy, while the high effectiveness projections correspond to the case in which containment measures reduce the reproduction number significantly — that is the situation in which the policy has had large positive impacts to reduce the effective rate of reproduction (see table 1). Our low policy effectiveness scenario translates the instance in which, on the contrary, the impact of each policy on the reproduction number is minimal.

Figure 4.2: Timing of Policies Across Countries

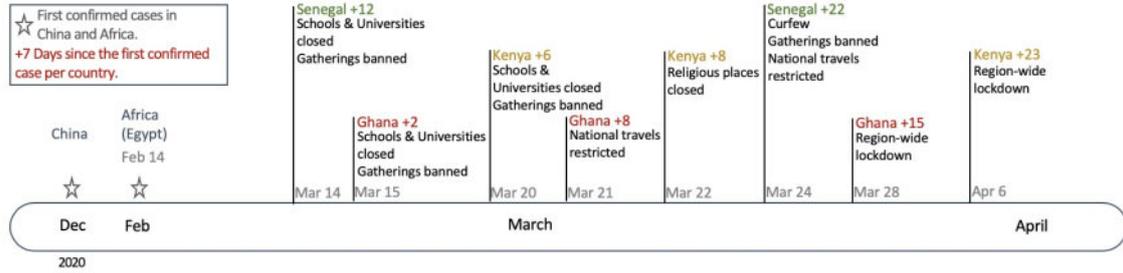


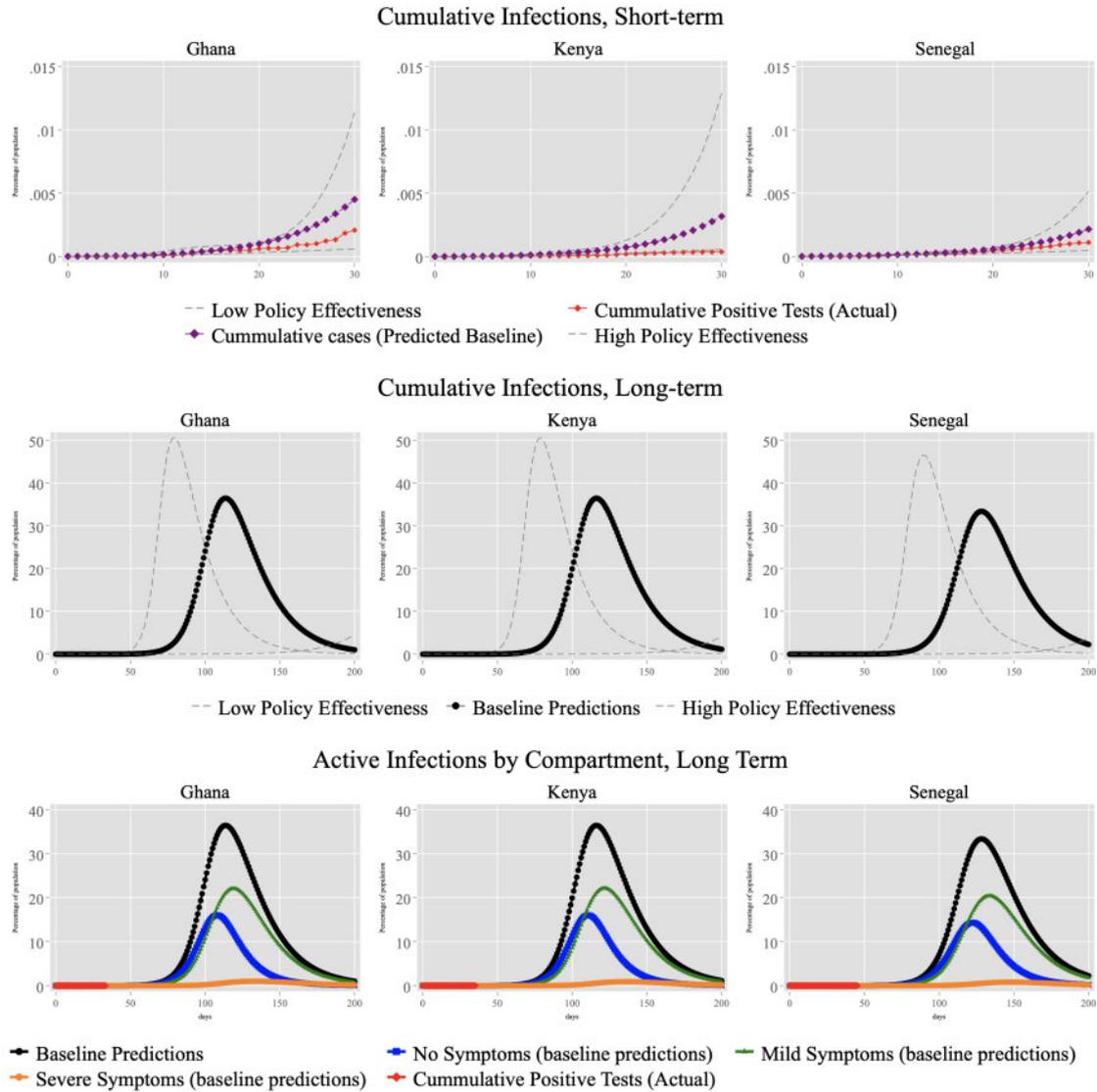
Table 4.1: Parameters of the Model

	GHANA	KENYA	SENEGAL	SOUTH KOREA	SOURCE
1 <sup>st</sup> positive case					European CDC (2020), Sen. Ministry of Health (2020),
Population	30.497 Millions	51.808 Millions	17.354 Millions	51.410 Millions	CountryMeters (2020)
$\mu_{birth}$	9.01e-5	9.71e-5	1e-4	2.51e-5	CountryMeters (2020)
$\mu_{death}$	1.91e-5	1.64e-5	1.6e-5	1.6e-5	The World Bank (2020)
$r_{as}$	0.4	0.4	0.4	0.4	Nishiura et al. (2020)
$T_{rec,as}$	14d	14d	14d	14d	Hubei: McIntosh (2020)
$T_{inc}$	5d	5d	5d	5d	McIntosh (2020)
$T_f$	6d	6d	6d	6d	McIntosh (2020)
$T_{rec,ms}$	16d	16d	16d	16d	McIntosh (2020)
$T_{sev}$	5d	5d	5d	5d	McIntosh (2020)
$T_{rec,ss}$	18d	18d	18d	18d	McIntosh (2020)
$\alpha$	2	2	2	2	McIntosh (2020)
$d_{ms}$	0.37%	0.37%	0.37%	0.03%	CountryMeters (2020)
$d_{ss}$	2%	2%	2%	1.04%	
$r_{ms}$	98.34%	98.53%	98.62%	94.33%	Verity et al. (2020)
$R_t$	1.25, (1.0-1.4) for $0 \leq d < 7$ 2.35, (2.2-2.7) for $7 \leq d < 9$ 2.3, (1.7-2.5) for $9 \leq d < 16$ 1.6, (1.0-2.2) for $16 \leq d$	2.4, (2.2-2.6) for $0 \leq d < 7$ 2.15, (1.8-2.5) for $7 \leq d < 9$ 2, (1.6-2.4) for $9 \leq d < 14$ 1.6, (1.0-2.2) for $14 \leq d$	1.29, (1.1-1.48) for $0 \leq d < 20$ 2.4, (2.1-2.70) for $20 \leq d < 26$ 1.5, (1.0-2.00) for $26 \leq d$	1.13 for $0 \leq d < 30$ 3.04 for $30 \leq d < 41$ 1.87 for $41 \leq d < 44$ 0.9 for $44 \leq d < 49$ 0.3 for $49 \leq d < 59$	Author's estimates, adjusting $R_t$ with timeline of govt. policies outlined in fig.4.2
$\beta_{ms}$	$0.41\beta_{as}$	$0.41\beta_{as}$	$0.41\beta_{as}$	$0.41\beta_{as}$	Author's estimates, using Wang et al. (2020)
$\beta_{ss}$	$\beta_{as}/T_{rec,ss}$	$\beta_{as}/T_{rec,ss}$	$\beta_{as}/T_{rec,ss}$	$\beta_{as}/T_{rec,ss}$	

Notes:  $R_t$  in parenthesis are  $R_t$  values for optimistic and pessimistic scenarios respectively.

Results reported in figure 3 show how the predictions fit the detected cases in the early days of the pandemic.

Figure 4.3: Projection of Active Infections



We report predictions for a year (see figure 3). Under the assumptions of the baseline model and their limitations, we predict that the peak of the epidemic will occur in July for all three countries as detailed in table 2. For Ghana, Kenya, and Senegal respectively, this peak should lead to approximately 11.1, 18.9, and 5.8 million active infections (including asymptomatic, and symptomatic cases) at the peak of the epidemic, with 308, 465, and 138 thousand individuals severely ill needing medical attention (see figure 3).

These long-term scenarios should be interpreted with great caution as they do

not consider future policies or actions that could drastically reduce the contact rates and subsequently, flatten the curve further .

Table 4.2: Projections of Active Cases at the Peak of the Epidemic for each Infected Compartment

		Days since first case	Active Cases at Peak		
			Severe symptoms	Mild symptoms	No symptoms
Ghana	Low Policy Effectiveness	79	0.4M	9.1M	7.7M
	Baseline	114	0.3M	6.7M	4.9M
	High Policy Effectiveness	250	0.1M	2.7M	1.6M
Kenya	Low Policy Effectiveness	79	0.6M	15.4M	13.1M
	Baseline	116	0.5M	11.7M	8.3M
	High Policy Effectiveness	252	0.2M	4.6M	2.7M
Senegal	Low Policy Effectiveness	90	0.2M	4.8M	3.9M
	Baseline	128	0.1M	3.5M	2.5M
	High Policy Effectiveness	254	0.1M	1.5M	1.0M

Note: The peaks of each infection sub-compartment might not align.

### 3.2 Testing the Sensitivity of the Simulations to $R_t$

We perform a sensitivity analysis for  $R_t$  on our baseline model. We perturb it 100 times by  $\varepsilon$  drawn uniformly in  $[5\%R_t, +5\%R_t]$ . The number of infections at the peak fluctuates between 27% to 40% of the total population in the active infection compartment for Ghana, between 28% and 40% for Kenya and between 25% to 37% for Senegal (see figure 2 of the appendix). In countries that enforced strict social distancing measures, predictions were significantly updated down — from about 2.2 million deaths on March 16 (Ferguson et al. 2020), to about 60 thousand on March 30 (Team and Murray 2020). A similar update can be expected from the outputs of our model as authorities take effective measures to reduce  $R_t$  and/or people in these countries gradually adopt behavior that would minimize contacts.

### 3.3 Population Density and Rate of Reproduction

As the population density increases, the rate of transmission of infectious diseases increases (Heesterbeek and Dietz 1996). With respectively 43.3%, 72.2%, and 50.6% as a share of their population living in rural areas, Ghana, Kenya, and

Senegal have sparsely populated areas outside of their main metropolitan areas, compared to countries like South Korea (18.5% of rural population).

There is little information on the relative rate of transmission of COVID-19 between rural and urban areas but we draw on other diseases, for which there is available data. During the 2014 Ebola outbreak in Sierra-Leone (Yang et al. 2015), we find that the basic reproduction number in Kambia (the least densely populated district of Sierra-Leone) is .56 times the one of the Western Area Urban district (the most densely populated district, that comprises the capital Freetown). We take that to mean that the  $R_t$  in rural areas was .56 times that of urban areas. Other mostly rural districts had a higher  $R_t$ . To mirror the range of ratios of reproduction rates observed in mostly rural and mostly urban districts for the Ebola epidemic in Sierra Leone, we run two simulations, one in which the rural to urban ratio is .50, and one where it is .75. These two ratios bound the difference between mostly rural districts and mostly urban areas for Ebola in Sierra Leone (Yang et al. 2015). Using these ratios, we calibrate the rural and urban reproduction rates so their population-weighted average is equal to the national  $R_t$  which we keep constant across our baseline scenario and this scenario:

$$\begin{cases} R_{t,rur} = \gamma R_{t,urb} \\ R_t = r_{urb} R_{t,urb} + (1 - r_{urb}) R_{t,rur} \end{cases}$$

Where  $R_{t,rur}$  and  $R_{t,urb}$  are the rural and urban reproduction rates respectively;  $\gamma = .50$ , or  $\gamma = .75$ ;  $r_{urb}$  is the national urbanization rate;  $R_t$  is the national reproduction rate listed in table 1. We use the first day of the first community transmission as the day of the first case in the rural area. Results are compiled in table 3. Effectively, we see in figure 4 that when accounting for rural areas, we observe two peaks. The first peak is driven by the spread in urban areas while the second peak, delayed in time is driven by the spread in rural areas. Kenya, with a rural share of the population of over 70% has the most noticeable split across its rural and urban areas.

### 3.4 Co-Morbidity and Rise in the Occurrence of Severe Symptoms

Co-morbidity can impact the share of mild cases that develop severe symptoms (Zhou et al. 2020). In Asia and Europe, hypertension, obesity, diabetes, and coronary heart diseases have been drivers of adverse health outcomes (Zhou et al. 2020, Grasselli et al. 2020). Because the combined prevalence of diabetes, hypertension and obesity are not higher in Ghana, Kenya, and Senegal than they are in regions we use to derive the recovery rates, the baseline simulations already account for them. However, Ghana, Kenya, and Senegal have a persistent and high rates of anemia and tuberculosis (Lancet 2020) (see table 6). To our knowledge, there is no study on the magnitude of the impacts of anemia, tuberculosis, or HIV on the recovery of patients who have contracted the virus. We simulate two scenarios, with 25% and 75% of the recovery rate of otherwise healthy individuals for individuals with one of these underlying conditions<sup>1</sup> (see table 5). In comparison, Zhou et al. (2020) find that in Wuhan, China, patients with comorbidities (hypertension, diabetes, coronary heart disease, chronic obstructive lung disease, carcinoma, chronic kidney diseases and others) have a recovery rate equal to 73.2% of their otherwise healthy counterparts. Though uncertain for HIV, anemia and TB, the impact of these underlying conditions on the recovery of individuals will likely lie between these two bounds. This translates into adjusting  $r_{ms}$  for individuals with TB, HIV, and anemia. Co-morbidities have age-specific incidence rates; anemia affects women of child bearing age primarily, while HIV affects young adults at higher rates. The prevalence of HIV, TB and anemia are extracted from the open database Global Burden Disease (GHDx 2020). We account for these age-based differences to compute the recovery rate of the population accounting for comorbidities:

$$r_{ms} = \sum_{ag} w_{ag} r_{ag}(1 - i_{morb}, x_{ag,morb})$$

Where  $r_{ms,morb}$  is the rate of recovery for infected individuals who develop mild symptoms and have one of the three comorbidities.  $r_{ag}$  is the recovery rate of the otherwise healthy individuals in the age-group,  $i_{morb}$  is either 1-0.25 or 1-0.75 depending on the scenario, and  $x_{ag,morb}$  is the share of individuals in each age-group with the comorbidity.

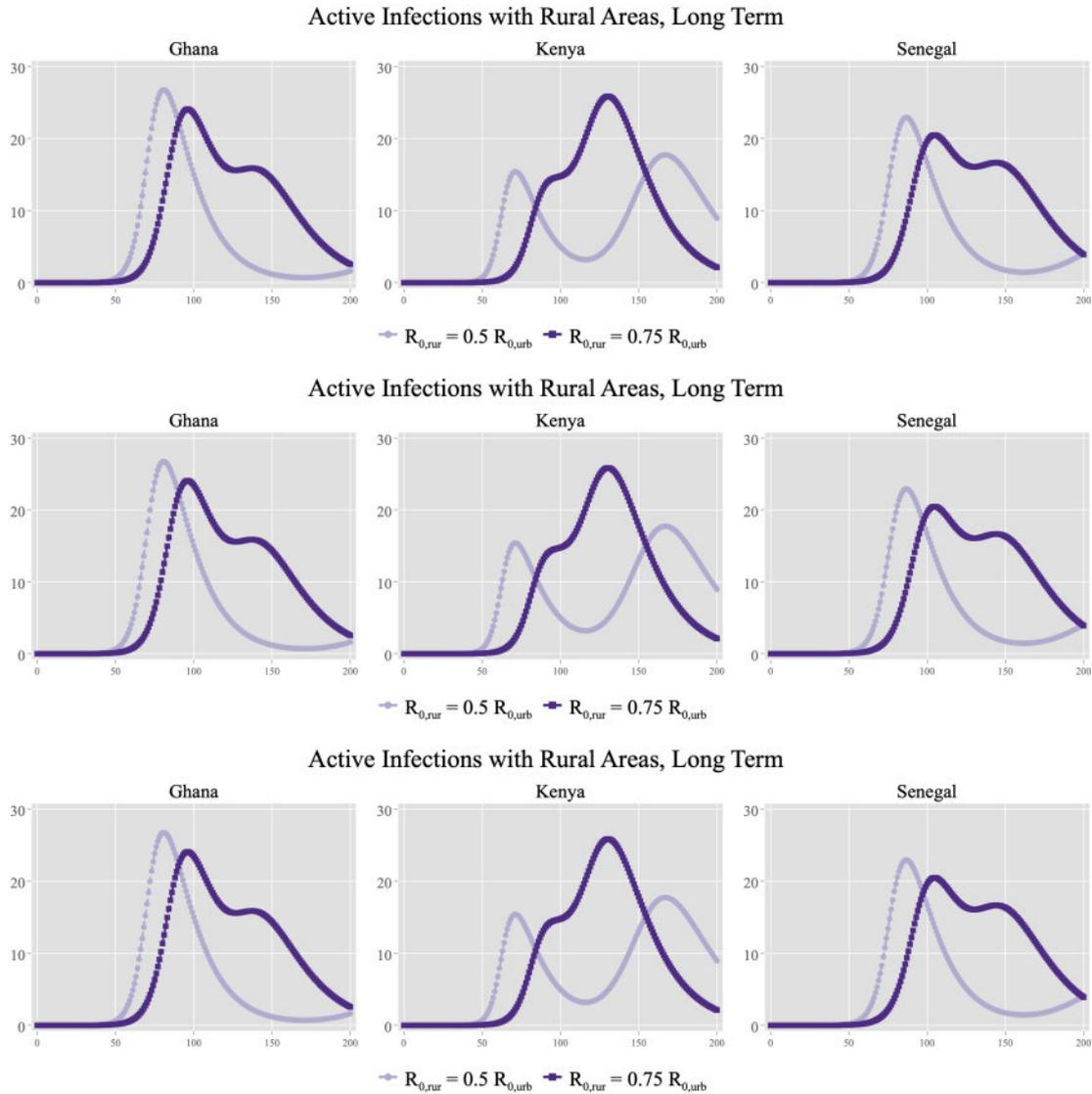
We report the results in figure 4 and table 3. As expected, the predictions are higher in the case where we assume that individuals with comorbidities have a rate of recovery that is 25% that of otherwise healthy individuals. In the scenario with  $R_{t,rur} = .75R_{t,urb}$ , the number of active severe cases at the peak is 0.242M with a 75% recovery scenario for Ghana (0.308M for the 25% scenario), 0.313M for Kenya (0.631M) against and 0.104M (0.145M) for Senegal. Kenya's large impact is driven by its larger HIV positive population.

Table 4.3: Projection of Infections Accounting for Africa Specific Factors

	$\frac{R_t(rural)}{R_t(urban)}$	Co-morbidity							
		% of the survival rate of healthy patients							
		75%				25%			
		Severe	Mild	Asympt.	Days*	Severe	Mild	Asympt.	Days*
Ghana	50%	0.3M	2.0M	1.3M	212	0.4M	1.8M	1.2M	215
	75%	0.3M	2.7M	1.8M	160	0.6M	2.5M	1.8M	162
Kenya	50%	0.4M	1.7M	1.1M	379	0.6M	1.2M	0.9M	413
	75%	0.2M	1.1M	0.7M	295	0.4M	0.9M	0.7M	311
Senegal	50%	0.1M	0.6M	0.4M	265	0.2M	0.5M	0.4M	275
	75%	0.2M	1.0M	0.7M	183	0.3M	0.9M	0.7M	187

\*Days of total infection peak, since first case tested positive  
 Note: The peak of each infection sub-compartment might not align.

Figure 4.4: Projected Active Infections Accounting for Underlining Conditions and Rural Areas



### 3.5 Mirroring South Korea's effectiveness

Unlike countries in Europe, Ghana, Kenya, and Senegal have taken containment measures very early in the progression of the disease. The policies could have had impacts similar to the ones in South Korea. We present results of simulations mirroring the  $R_t$  for South Korea. Specifically, we decrease  $R_t$  for each country three weeks after the last recorded policy to 0.88, and then again at 6 weeks to 0.3. We find that the peak is much lower, with a number of active severe infections at the peak between 166 and 214 individuals for Ghana, 208 and 286 individuals for

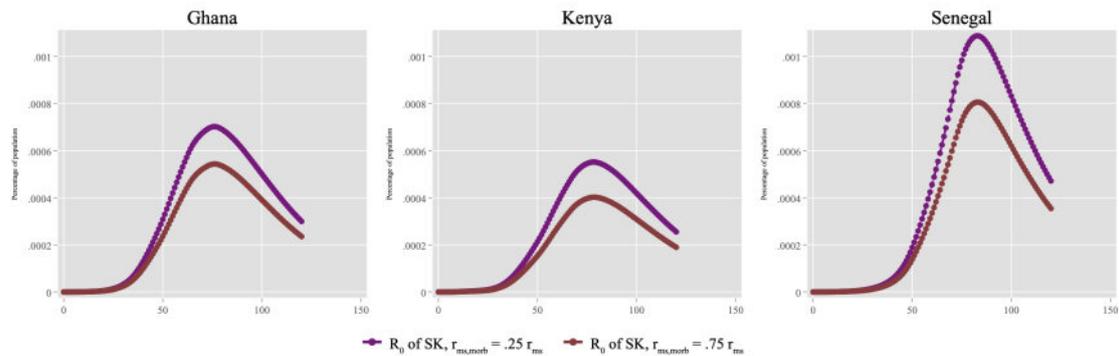
Kenya, and 140 and 189 individuals for Senegal; with the two bounds being a for recovery rates of respectively 75% and 25% of the recovery rate otherwise healthy patients. These peaks will occur two to three months after the first case (see figure 5). This scenario is attainable only if these countries are able to maintain effective policies for an extended period.

Table 4.4: Projection of Active Cases At Peak Accounting of Co-morbidities, With South-Korea's  $R_t$

$\frac{R_t(rural)}{R_t(urban)}$	Co-morbidity								
	% of the survival rate of healthy patients								
	75%				25%				
		Severe	Mild	Asympt.	Days*	Severe	Mild	Asympt.	Days*
Ghana	100%	166	3,164	2,428	51	214	3,110	3,110	57
Kenya	100%	208	4,221	3,206	60	286	4,134	4,134	60
Senegal	100%	140	3,253	2,661	69	189	3,183	3,183	69

Note: The peak of each active cases for each sub -compartment might not align.

Figure 4.5: Projected Severe Active Infections Mirroring South Korean's  $R_t$



## 4 Discussion

In this study, we account for the age structure of the population in each country, the burden of potential comorbidities and the differential spreads of the virus in rural and urban areas. We find that the relatively young population may limit the severity of the epidemic, by lowering the number of infections that lead to severe

symptoms. We also find that sparsely populated areas may limit the spread of the epidemic. Rural areas effectively may lead to staggered peaks; this has important implications for policy makers who may be faced with two waves, and so may need to adapt their responses to adaptively deploy personnel on their territory as these peaks occur. High rates of comorbidities however may lead to more individuals developing severe symptoms relative to a scenario with no comorbidities. We find that at the peak Ghana, Kenya, and Senegal are predicted to have respectively between 0.78 and 1.03%, 0.89 and 1.22%, and finally, 0.60 and .84% active clinical severe cases of COVID-19 with a peak of total infections predicted to occur between June 2 and June 17 (Ghana), July 22 and August 29 (Kenya), and May 28 and June 15 (Senegal) respectively against a July timeline for our baseline specification. Successful containment policies could lead to even lower rates of severe infections.

Though recent models look at a few countries in Africa ([Zandvoort et al. 2020](#)), or at the continent as a whole ([Pearson et al. 2020](#), [Uneca 2020](#)), there are little to no studies predicting the spread of COVID-19 in Ghana and Senegal while incorporating specificities of these two countries. In Kenya, however [Brand et al. \(2020\)](#) account for age-based population mixing and assume that asymptomatic individuals are as infectious as symptomatic individuals to predict that by the end of the year, 46.1 million (i.e. 89% of the public) of infections will have occurred. This prediction is comparable with the baseline results of our study in the absence of further containment policies. In that scenario, we find that about 47.7 million (93% of the public) individuals may be infected cumulatively.

Containment measures will be successful only if the public complies; however, measuring compliance is complex and has not been rigorously studied in the context of COVID-19 in these countries. In Ghana, Kenya and Senegal poverty is the main challenge to compliance, with official unemployment rates reaching 68.7%, 51.3% and 64.6% respectively ([The World Bank 2020](#)). As a response, authorities have implemented emergency transfer programs in cash and in-kind to the most vulnerable households partly to address compliance but also to avoid a humanitarian crisis (Senegal, Ghana). In urban areas, officials have required buses and taxis to reduce their number of passengers (Kenya, Senegal) and have

mandated the use of masks (Ghana, Senegal).

Looking at how spike in cases was met by various healthcare systems in Europe and Asia, it is likely that most asymptomatic and mild cases may remain undetected.

## 4.1 Limitations

Our model does not incorporate changes in the survival rate of the virus due to weather or humidity, and in that regard, our simulations are a worst-case scenario (Wang et al. 2020, Sajadi et al. 2020). Additionally, the model assumes homogeneous mixing of individuals within rural areas and urban areas which is an unlikely assumption. In a future iteration of our model, we plan to use a spatially-structured model in order to relax the homogeneous mixing assumption by leveraging phone data (Prem et al. 2017, Dong et al. 2019, Oliver et al. 2020).

The model also excludes international population flows. All countries in our sample have closed their international borders — airports and roads — before or a few days after their first confirmed imported case (see figure 2). However, it is possible that COVID-19 was spreading undetected for days in the respective countries. If that is true, the peak of active cases might be delayed in comparison to the true peak. Furthermore, the spread of this disease is highly dependent on the reproduction number  $R_t$ . Since this number is contingent upon many factors (policies, individuals' behavior etc.); its value in the long-run is subject to large uncertainties. The projected number of infections in the medium to long term could thus be considerable overestimates (or underestimates) of the true number of infections (depending on the scenarios).

These predictions are aggregating infections in rural and urban areas, however, in practice, the peaks in urban areas, due to higher reproduction rates, will occur earlier. In rural areas however, the peaks will be delayed due to their lower  $R_t$ . This distinction is important for policy makers who can target their resources accordingly.

The use of the data also comes with limitations such as the inaccuracy of the data collection. For example, one person was tested positive for COVID-19 on March 4

but entered Senegal on February 24. We expect that all the countries in our sample are dealing with similar delays, however, we did not find a consistent way to address this issue. Additionally, given the low number of tests performed to detect the virus, we cannot ex-ante measure the accuracy of our model in Ghana, Kenya, and Senegal.

Because outcomes of individuals with critical needs are highly dependent on the capacity of health care systems, having data on health care capacity is important in predicting the number of fatalities. In our simulations, information such as the number of intensive care unit beds would inform the fatality rate of individuals with severe symptoms ( $d_{ss}$ ). Unfortunately, we do not have access to such data and we thus choose not to show the results for fatalities rates in these three countries. Finally, we use a SIR, which assumes perpetual immunity – however, there are still uncertainties regarding the possibility of reinfection ([Mahase 2020](#)).

## 5 Conclusion

In conclusion, containment measures, age structures, low urbanization and co-morbidity may lead Ghana, Kenya, and Senegal to having different trajectories from Asian, European countries and the USA. This study is a first attempt at accounting for rural densities and co-morbidity, and it suggests that rural areas will slow down the spread of the epidemic, and that relatively young population will keep the number of severe cases low compared to the nearly 3.5% hospitalization rate in Europe and central Asia ([Walker et al. 2020](#)).

Our findings also show how sensitive these results are to different assumptions on the effectiveness of policies, assumptions on co-morbidities and differential effective rates of reproduction in rural and urban areas.

## Appendix A4. Chapter 4

Figure A4.1: Visual representation of the model

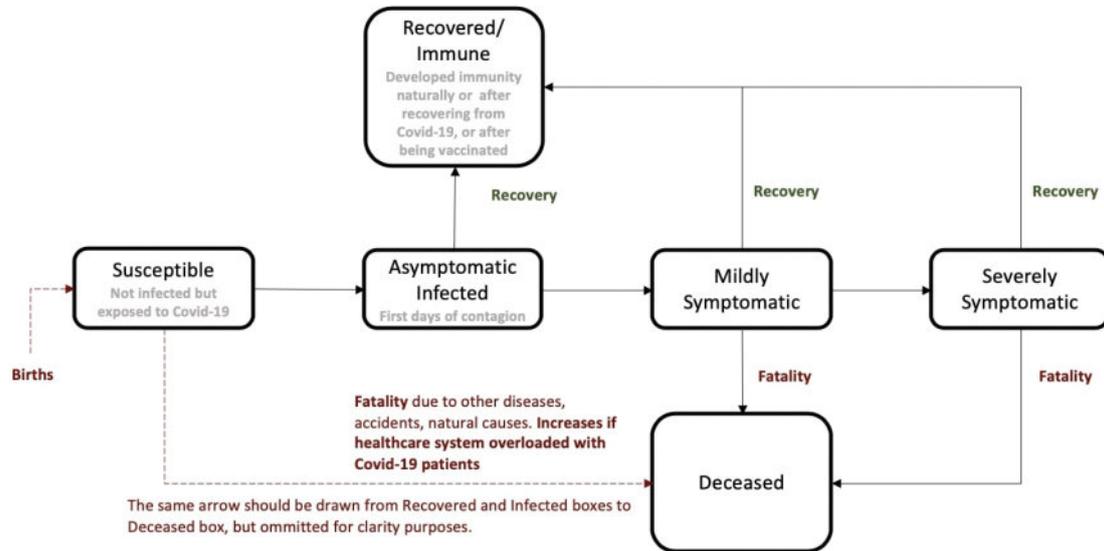


Figure A4.2: Sensitivity of Active Cases to Perturbations of  $R_t$

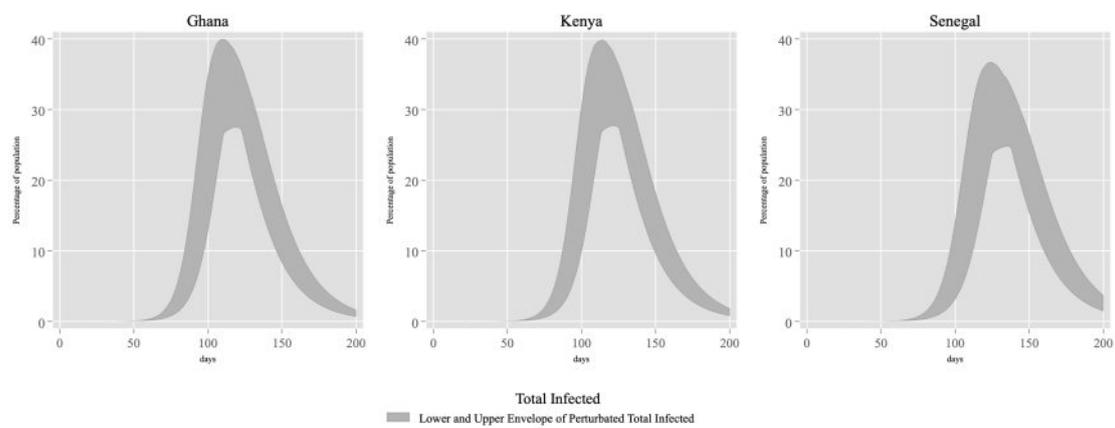
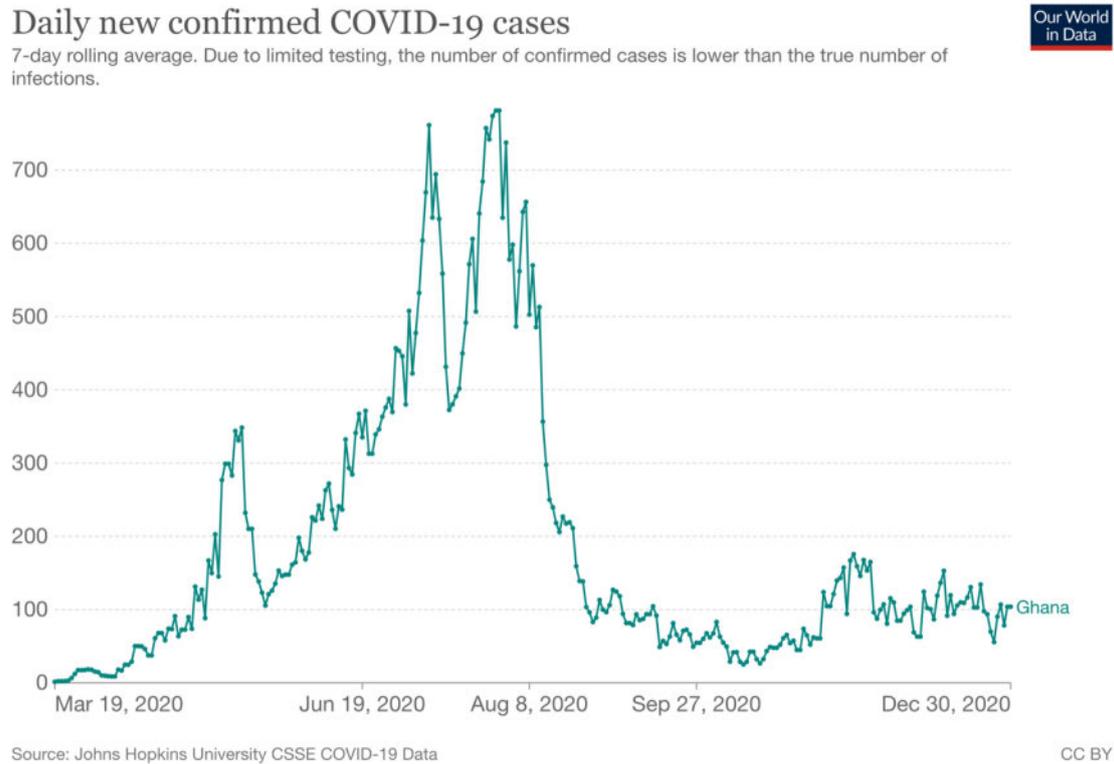


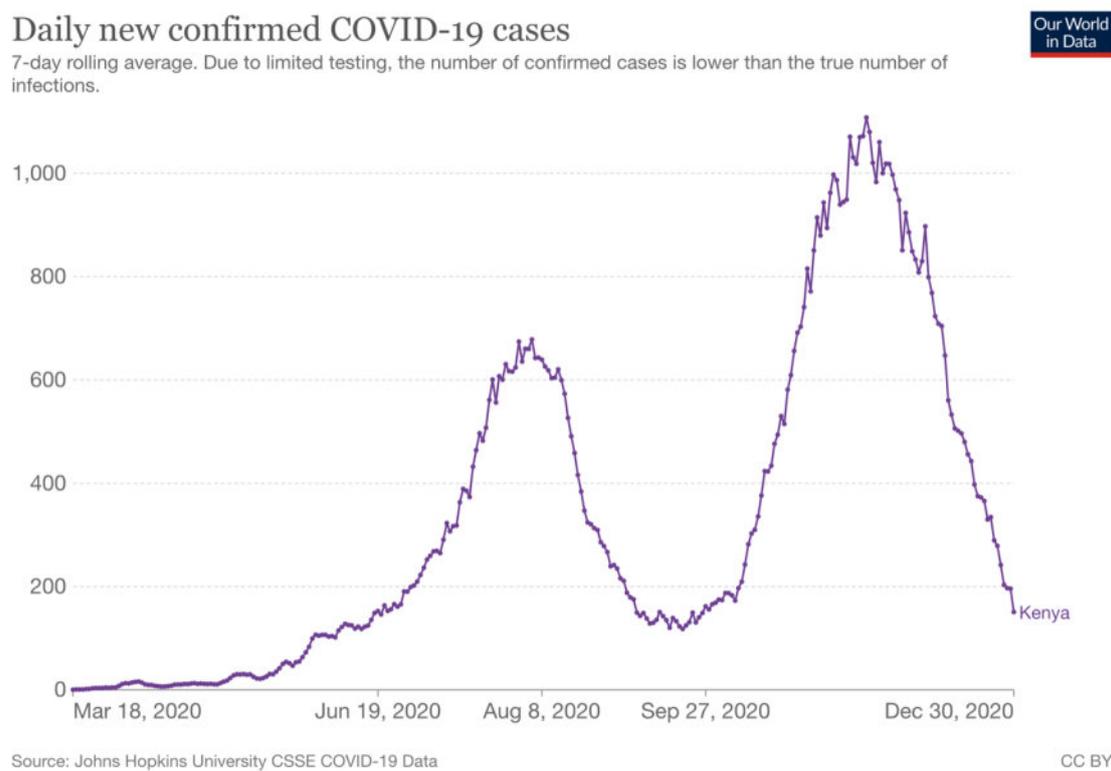
Figure A4.3: Daily new confirmed Covid-19 cases in Ghana (update August 2022)



Source : [Dong et al. \(2020\)](#).

Note: Graph by OurWorldinData. Figure 4.4 predicted daily confirmed cases. This graph represents the actual 7-day rolling average of new confirmed Covid-19 cases in Ghana from May 19th to December 30th 2020. Data were not available before May, 19th 2020.

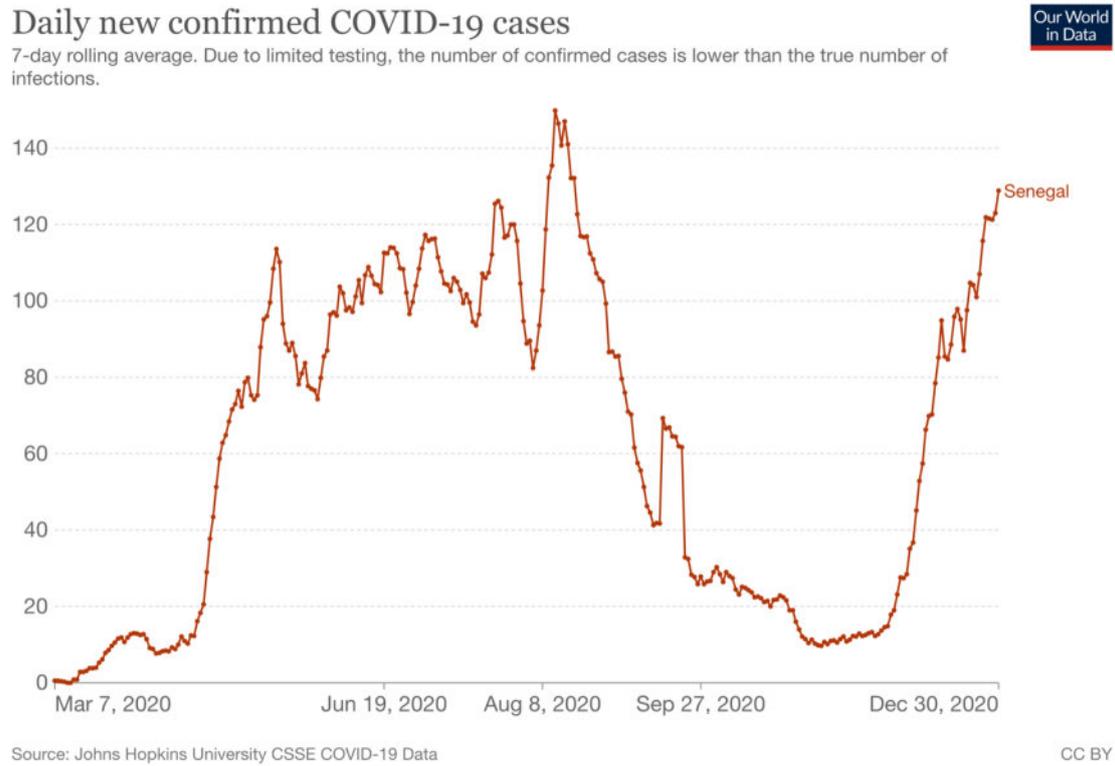
Figure A4.4: Daily new confirmed Covid-19 cases in Kenya (update August 2022)



Source : [Dong et al. \(2020\)](#).

Note: Graph by OurWorldinData. Figure 4.4 predicted daily confirmed cases. This graph represents the actual 7-day rolling average of new confirmed Covid-19 cases in Kenya from May 18th to December 30th 2020. Data were not available before May, 18th 2020.

Figure A4.5: Daily new confirmed Covid-19 cases in Senegal (update August 2022)



Source : [Dong et al. \(2020\)](#).

Note: Graph by OurWorldinData. Figure 4.4 predicted daily confirmed cases. This graph represents the actual 7-day rolling average of new confirmed Covid-19 cases in Senegal from May 7th to December 30th 2020. Data were not available before May, 7th 2020.

Table A4.1: Projection of Active Cases Accounting for Co-morbidity or Rural/Urban factors

			Active cases at peak			
			Days since	Severe	Mild	No
			first case	symptoms	symptoms	symptoms
Ghana	Rural/Urban*	50%	81	0.2M	4.8M	3.9M
		75%	96	0.2M	4.4M	3.4M
	Co-morbidity**	25%	114	0.5M	6.6M	4.9M
		75%	114	0.4M	6.7M	4.9M
Kenya	Rural/Urban	50%	167	0.2M	5.7M	4.2M
		75%	130	0.4M	8.2M	5.3M
	Co-morbidity	25%	116	0.8M	11.3M	8.3M
		75%	116	0.6M	11.4M	8.3M
Senegal	Rural/Urban	50%	87	0.08M	2.4M	1.9M
		75%	105	0.09M	2.2M	1.6M
	Co-morbidity	25%	129	0.2M	3.5M	2.5M
		75%	128	0.2M	3.5M	2.5M

\*  $\frac{R_t(rural)}{R_t(urban)}$ 

\*\* Recovery rate for patients with preexisting conditions as percentage of healthy patients recovery rates

Note: The peak of each active cases for each sub-compartment might not align

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## Investissement en santé préventive et biais comportementaux par Clémence Pougé Biyong

Les régions du monde où le reste-à-charge est encore la principale source de financement du système de santé sont particulièrement vulnérables au sous-investissement dans la santé préventive. Cette thèse propose quatre articles empiriques pour analyser les raisons de ce sous-investissement par le prisme des biais comportementaux et, pour contribuer à mieux définir les politiques publiques. Le Chapitre 1 montre qu'entre 2000 et 2016, au Malawi, les individus exposés à des programmes de prévention VIH financés par l'aide internationale ne se sont pas significativement plus dépistés que ceux qui n'étaient pas exposés. Par contre, la stigmatisation a augmenté dans les régions qui ont été exposées auxdits programmes. Le Chapitre 2 analyse l'adoption d'un traitement préventif avec un modèle de choix discrets qui intègre le paramètre du comportement à risque. Les faits stylisés théoriques sont ensuite testés grâce un modèle d'équations simultanées et à une base de données longitudinale inédite collectée auprès de travailleuses du sexe en Côte d'Ivoire. Cette étude montre que la décision d'adhérer au traitement préventif dépend du niveau de risque dans le comportement sexuel et invite à relativiser la menace de comportement de compensation des risques. Dans un contexte de croissance du taux d'obésité, le Chapitre 3 analyse l'effet d'une taxe sur les boissons sucrées comme un choc intra-utero sur la santé des enfants, au Mexique. Ce chapitre montre que la politique fiscale n'est pas suffisante pour infléchir le comportement nutritionnel des mères et améliorer la santé des enfants. Enfin, le dernier chapitre a été écrit au coeur de la pandémie de Covid-19 pour prédire la propagation du virus au Ghana, Kenya et Sénégal. Il propose un modèle susceptibles-infectés-rétablis en prenant en compte les caractéristiques invariantes dans le temps des pays étudiés et l'hétérogénéité du statut infectieux des individus. Ce chapitre montre que le fait d'avoir une population jeune et une population essentiellement rurale limite la propagation et la sévérité de la pandémie dans les pays étudiés.

**Mots-clés :** santé préventive, biais comportementaux, comportements à risque, VIH, obésité, Covid-19.

**Classification JEL :** I1, D01, D9, H20.