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Essays in industrial organization, with applications to the electricity and digital markets

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Résumé

Cette thèse mobilise les outils de l'Economie Industrielle pour appréhender deux transformations majeures en cours dans notre économie: la transition énergétique et la révolution numérique.

La première partie de cette dissertation vise à proposer une architecture de marché permettant à la transition énergétique de se faire de manière aussi efficace économiquement que possible. En effet, le déploiement sans précédent des énergies renouvelables, et l'apparition de technologies innovantes comme les compteurs intelligents ont pour conséquence une forte décentralisation de l'offre et de la demande d'électricité, nous éloignant de plus en plus du modèle traditionnel. Ce nouveau paradigme induit aussi des défis importants liés à la variabilité et l'imprévisibilité des nouvelles sources de production d'électricité. Cette partie vise à fournir des outils permettant de maintenir ou d' améliorer la flexibilité des systèmes énergétiques en vue de ses transformations. Elle est organisée en deux chapitres.

Le premier chapitre, écrit avec Thomas-Olivier Léautier, étudie l'effet des mécanismes de soutien à la capacité sur le bien-être social, lorsque plusieurs marchés de l'énergie sont physiquement interconnectés. Par souci de simplicité, nous nous plaçons dans un environnement de marchés sans barrières à l'investissement. Un sous-investissement peut cependant être observé, en raison d'un problème bien connu de "missing money", induit par la présence d'un plafond de prix sur les marchés de gros de l'énergie. En conséquence, certains régulateurs peuvent juger le niveau de sécurité d'approvisionnement insuffisant. Comme cela a été le cas dans de nombreux pays au cours des dix dernières années, ils peuvent alors décider d'intervenir au moyen d'un mécanisme de soutien à la capacité, afin d'atteindre des objectifs de sécurité d'approvisionnement préalablement définis. Nous démontrons que si les Gestionnaires de Réseau de Transport (GRTs) ne sont pas autorisés à réduire la capacité d'export vers d'autres régions et que le marché voisin reste "energy-only", le marché de capacité est inefficace, sauf si la capacité d'interconnexion est faible. En effet, les marchés interconnectés ne forment ainsi qu'un seul marché et un

déplacement physique de capacité ne se traduit pas nécessairement par une augmentation des délestage. Si au contraire les GRTs peuvent réduire la capacité d'export lorsque la demande sur leur zone d'équilibrage est élevée, le marché ayant mis en place un mécanisme de capacité attire les investissements. Sur le long terme, la sécurité d'approvisionnement du marché voisin se voit donc réduite. Un marché voisin qui serait "energy-only" ou aurait fait le choix d'une réserve stratégique sera alors lésé, et pourrait se trouver contraint d'intervenir à son tour afin d'atteindre ses propres objectifs en matière de sécurité d'approvisionnement. Le moyen le plus efficace économiquement sera alors de mettre en place un marché de capacité également. Ainsi, les mécanismes de capacité pourraient se multiplier en Europe en raison de leurs effets négatifs sur l'investissement dans les régions voisines. Ce résultat est en rupture nette avec la conviction commune, fondée sur des raisonnements valides sur le court terme, qui veut qu'un marché "energy-only" profite de la sécurité d'approvisionnement fournie par un éventuel mécanisme de capacité voisin. Nos conclusions appellent à l'harmonisation des mécanismes de capacité en Europe.

Le second chapitre étudie la manière dont les incitations à l'effacement de la demande peuvent s'intégrer dans les mécanismes de capacité. Lorsque la capacité de génération est jugée insuffisante, deux stratégies sont en effet possibles. La première consiste à augmenter la capacité de génération disponible au moyen d'un mécanisme de capacité –comme vu dans le chapitre précédent. Il est aussi possible d'atténuer les pics de demande en déployant les technologies d'effacement. La solution la plus efficace économiquement est probablement de mettre en place ces deux stratégies simultanément. J'interroge donc comment les incitations à l'effacement de la demande peuvent s'intégrer dans les mécanismes de capacité, et formule le paiement dû à ces technologies, au titre de leur contribution à la sécurité d'approvisionnement. Je montre que si l'effacement n'est pas sensible au prix, mais au contraire est activé sur demande du GRT, sa contribution à la sécurité d'approvisionnement est moindre que les moyens de génération traditionnels produisant une électricité à un coût marginal moindre que le plafond de prix. Mes résultats confirment que tous les moyens de génération effectivement activés lors des pics de demande doivent recevoir le même paiement au titre de la capacité. Cependant, le paiement aux technologies d'effacement doit être stable ou diminuer à mesure que la position de l'opérateur d'effacement gagne en priorité de service lors d'opérations délestages. Dans le cas de technologies d'effacement stylisées, correspondant à des propensions à accepter le délestage propres à chaque consommateur-effaceur, je propose un menu de contrats qui induit un investissement optimal dans l'effacement. J'observe finalement que les incitations que proposent les mécanismes existants aux technologies d'effacement non sensibles aux prix sont inadéquates. Afin d'atteindre l'optimalité des investissements dans les technologies d'effacement, je propose d'appliquer un facteur de réduction simple à ces technologies, en fonction des périodes d'activation attendues.

Le passage aux technologies numériques sera un facteur clé de la transformation du secteur de l'énergie. Dans ce secteur comme dans d'autres, la transition vers ces technologies a vu le développement de nouvelles pratiques, qui sont au cœs ur de la deuxième partie de cette dissertation. Nous étudierons certains défis auxquels sont d'ores et déjà confrontées les plateformes d'intermédiation, en particulier les nouveaux problèmes concurrentiels et la confiance des utilisateurs dans ces nouveaux outils.

Le premier chapitre de cette partie étudie le mécanisme de référencement croisé entre plateformes numériques concurrentes. Il consiste généralement à l'insertion de liens dans les pages internet des plateformes qui renvoient leurs utilisateurs vers des plateformes concurrentes. Mon modèle théorique démontre que ces liens induisent un effet de partage de marchés qui atténue la concurrence, ce qui cause *in fine* une diminution de la qualité des contenus proposés aux utilisateurs. De manière surprenante, le bien-être des utilisateurs peut lui aussi diminuer si l'effet négatif sur la qualité l'emporte sur l'effet positif constitué par la mise à disposition d'une plus grande quantité de contenu. Dans le domaine des médias, qui constitue mon exemple principal, je montre empiriquement que ces références aux concurrents sont extrêmement fréquentes. La sélection des articles suggérés à l'utilisateur tend à limiter l'effet de substitution d'une source d'information par une autre, et à augmenter le temps passé par les utilisateurs sur les sites d'information. J'observe en outre que les journaux en ligne délèguent la gestion des liens à des tierces parties. Je démontre que les frais facturés aux journaux en ligne par ces tierces parties atténuent les effets anti-concurrentiels des liens tout en préservant l'effet de quantité. Enfin, je montre que la concurrence entre plusieurs tierces parties résulte dans l'établissement à l'équilibre d'un niveau de frais élevé, en raison de la nature biface du marché de l'intermédiation. Cela maximise le bien-être des utilisateurs: des frais situés juste en deçà de la propension à accepter des plateformes autorisent la présence de liens tout en assurant que les plateformes préfèrent être l'origine plutôt que la cible du lien. Dans ce cas, les liens entre plateformes promeuvent à la fois la diversité et la qualité de contenu fournis par l'industrie numérique. De même, je montre que la concurrence entre tierces parties facilite l'entrée de nouveaux concurrents. Alors que les autorités de régulation cherchent de plus en plus activement des moyens d'améliorer la qualité des services numériques, mes résultats montrent qu'une attention particulière au marché des liens entre plateformes peut fournir des outils réglementaires particulièrement efficaces, fondés sur les mécanismes de marché.

Le second chapitre de cette partie, écrit avec Emil Palikot (Toulouse School of Economics), étudie l'effet du mécanisme de réputation de la plateforme Blablacar, sur la performance des utilisateurs issus de minorités. En exploitant un grand jeu de données inédit, nous montrons que les conducteurs issus de minorités affichent de moins bons résultats économiques que les autres conducteurs : par rapport aux utilisateurs non issus d'une minorité, leurs annonces sont moins consultées, ils vendent moins de sièges et génèrent moins de revenus. Nous démontrons cependant que le système de réputation –qui prend la forme d'une note et un commentaire laissés par les voyageurs à l'issue du voyage– contribue à réduire cet écart de performance. En effet, cet écart se concentre sur les premières interactions mais se réduit considérablement à mesure que le conducteur bâtit sa réputation. Ainsi, le système de réputation permet aux minorités de se soustraire en partie à la discrimination au fur et à mesure des interactions sur la plateforme. Dans un premier temps, nous isolons ce phénomène au moyen de modèles d'évaluation à forme réduite. Ensuite, un modèle de choix individuels discrets permet d'estimer les caractéristiques de la demande des passagers. Un modèle de préoccupations de carrière nous permet de déterminer les caractéristiques de l'offre, ainsi que les convictions du marché à propos de la qualité des conducteurs. Nous démontrons que les convictions des passagers sont fondées sur les caractéristiques sociodémographiques des conducteurs, puis sont révisées grâce aux commentaires reçus par ceux-ci. Notre étude attribue une grande proportion de l'écart de performance aux convictions biaisées et pessimistes concernant la qualité des conducteurs issus de minorités. Le système de réputation induit donc trois effets majeurs. Premièrement, il pousse les conducteurs à fournir un service de qualité. Cet effort constitue un coût pour tous les conducteurs. Deuxièmement, cet engagement à l'amélioration du service permet aux conducteurs d'augmenter leurs revenus, étant donné que les passagers valorisent la qualité améliorée du service rendu. Finalement, dans le cas de populations discriminées, le système de réputation permet aux conducteurs de révéler la qualité de leur service, et de corriger les convictions éventuellement biaisées des passagers. Nous quantifions ces trois effets et montrons que les minorités seraient les plus grands bénéficiaires d'une augmentation de la précision du système de réputation.

Acknowledgments

Starting a PhD after several years in consulting may seem like a strange idea. Doing it for the PhD itself with no particular intention to pursue in academia may seem even more suspicious, especially when one ventures into considerations about end-of-the-month accounting. However, I never regretted this choice for a second.

These years of doctoral research have undoubtedly been amongst the richest in my life. I got to meet exceptional people, and got opportunities no other environment could have provided to me. Thanks to these people I got caught up in the game, and staying in academia soon sounded like the right thing to do.

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Part I

Achieving resource adequacy when supply and demand are variable

Chapter 1

Cross-border effects of capacity remuneration schemes in interconnected markets: who is free-riding?

About this chapter

This chapter corresponds to a paper co-written with Thomas-Olivier Léautier (EDF and Toulouse School of Economics). The authors gratefully acknowledge the stimulating comments of Estelle Cantillon, Christophe Gence-Creux, and participants to the 13th International Conference on the European Energy Market, the 39th Annual IAEE International Conference, the 2016 FAEE student workshop, various internal seminars in Toulouse School of Economics and the French Directorate General of Energy and Climate. We also acknowledge the invaluable comments of three anonymous referees. At the time this dissertation was written, the paper was forthcoming in the Energy Journal.

Abstract

We study the welfare impacts of domestic support schemes for generation capacity when energy markets are interconnected. We find that if transmission system operators (TSOs) can't reduce export capacity and neighbors stay energy-only, a capacity market is ineffective unless transmission capacity is small. If TSOs can reduce export capacity, the capacity market attracts investments and Security of Supply (SoS) of non-domestic markets shrink. A neighboring energy-only or strategic reserve market will thus be prejudiced in the long-run and may have to implement a capacity market as well in order to meet its SoS standard. Hence, capacity markets may spread in Europe thanks to their negative cross-border effect on investment incentives. This is in sharp contrast with the conventional wisdom, based on short-term arguments, that energy-only markets will free-ride the SoS provided by neighboring capacity markets. Our conclusions urge for the harmonization of capacity remuneration schemes across Europe.

Keywords: Capacity markets, Energy markets integration, Capacity investment, Adequacy, Regulation.

1 Introduction

Since the liberalization process began in the early 90s, the European power sector has been increasingly exposed to market-based mechanisms, to replace national planning. Investments are increasingly market-driven, spot prices are supposed to induce a socially optimal capacity mix and adequacy level. However, the power market is still exposed to many constraints. The upstream market has so far remained very concentrated, while demand remains largely inelastic, requiring the implementation of numerous regulatory firewalls such as price caps, in a move to tame market power abuse. Regulators and researchers (Cramton and Stoft (2006)) have observed that the price signal alone does not generate the "adequate" level of capacity, as defined by their Security of Supply (SoS) standards. As a consequence, capacity remuneration mechanisms (CRMs) to directly remunerate installed capacity (and not only energy), are implemented or considered in the US and in Europe. In Europe, this leads to a patchwork of assorted and complex market designs– see Appendix A for a summary of current schemes in Europe. These regulatory interventions have so far been designed in an uncoordinated manner, as the combined effects of unprecedented penetration of renewable energy sources and low demand have pushed regulators to find a quick fix to support capacity. This regulatory intervention is very complex and somewhat controversial even when only one market is considered. Furthermore CRMs ignore cross-border effects or at best take imports into account in an implicit manner. We show this may prove very costly in the long run.

A specific concern is that consumers in a market without a CRM may free-ride on capacity payments by their neighbors who have a CRM. This paper proves that cross-border effects do exists, and they might be far from negligible. However it shows that the problem in the long-run does not lie so much in capacity free-riding (at the *expense* of consumers or producers in the market with a CRM), but rather in unfair investment competition (at the *benefit* of producers and in turn consumers in the market with a CRM). We will compare the benchmark case of an Energy-Only market without a support scheme (market "EO"), with a market providing a Capacity Market (market "CM") and with an energy-only market endowed with a Strategic Reserve (market "SR").

This paper focuses on the effect of capacity support schemes on investment in the long-run. Our main contribution to this heated debate is to provide an analytically rigorous discussion of the impact of CRMs in one market on a neighbouring market. The paper uses a highly stylized model that abstracts from many real life complications to focus on the key economic mechanisms. To focus on the main insights, no account is made of risk aversion, imperfect reliability of assets and we assume perfect competition (see e.g. Fabra (2018) for a discussion of the impact of market power on CRMs). Hence we model a market without any imperfection – except that policy makers want more demand coverage than what emerges without intervention.

We find several results. First, by construction of a model without risk-aversion nor any other imperfection, the Energy-Only market maximizes expected net surplus. The intuition for this result is that capacity payments are uniform: every MegaWatt of installed capacity receives the same per unit capacity payment, even though only a fraction of installed capacity is used in (almost) every state of the world. Therefore, the total capacity payment, which is proportional to total installed capacity, exceeds the net surplus generated by additional capacity, which is proportional to capacity actually used. To avoid the uniform payment issue, policy makers in some countries implement strategic reserves. Then, if Strategic Reserves and Capacity Markets lead to the same Security of Supply, hence the same installed capacity, they lead to the same expected net surplus.[1] The direct, upfront cost of capacity support is greater when the Security of Supply standards are met with Capacity Markets instead of a Strategic Reserve. However the energy prices are (weakly) higher with a Strategic Reserve. Hence, the higher upfront cost of implementing support through a capacity market (relative to a

[1]In a different context Léautier (2016) proves that this uniform payment explains why implementing a capacity market increases producers' profits, even though installed capacity increases.

strategic reserve) is offset indirectly, through smaller electricity bills.

Second, if markets EO and CM are interconnected, CM will export to EO, possibly at high prices: capacity in CM gets more profitable and the capacity payment can be scaled down. Conversely, investing in EO is less profitable due to CM's large (supported) operational capacity and less capacity will be built there. Market CM is thus better off when it has an energy-only neighbor than when it is isolated. EO is indifferent in terms of welfare, even though its SoS may be degraded if transmission system operators (TSOs) are allowed to reduce export capacity. If EO's SoS reaches unacceptably low levels, the energy-only market might be forced to implement a CRM as well.

Third, if TSOs are not allowed to reduce export capacity, the CRM merely displaces capacity, but has no long-run effect on Security of Supply. In that case, a market willing to increase its SoS through a capacity market will have an incentive to decrease its interconnection capacity with neighbors.

Finally, the Online Appendix[2] shows that implementing a capacity market in a market interconnected with a strategic reserve market yields similar results to the CM/EO case: CM's support scheme is alleviated by additional revenues when it exports at high prices to SR. If TSOs can reduce export capacity, SR has to build up strategic reserve by an amount equivalent to the increment of capacity in CM following the implementation of the capacity market, in order to maintain its SoS level. Table 1.1 summarizes the cross-border effects of CRMs, when there are no explicit corrective transfers from one scheme to the other, price cap is set at a (common) Value of Lost Load (VoLL), demand is perfectly symmetric (i.e. there are no aggregation gains) and TSOs are allowed to reduce export capacity:

[2] available at www.xavierlambin.wordpress.com/research

	effect of existence of a neighbor, on local scheme:		
	Local scheme is EO	**Local scheme is SR**	**Local scheme is CM**
neighbor is EO	neutral	welfare increase	welfare increase
neighbor is SR	welfare neutral, increased SoS	neutral	welfare increase
neighbor is CM	welfare neutral, decreased SoS	welfare decrease	neutral

Table 1.1: Gains from interconnection with neighbors with TSO intervention at times of scarcity and symmetric demand

The remainder of the paper is organized as follows. Section 2 reviews the literature. Section 3 outlines the benchmark model, when markets are isolated from one another. Section 4 analyses interconnected markets in the simple case when demand is same in both markets. We observe that an energy-only market endures decreased SoS when its neighbor implements a capacity market. Possible solutions to mitigate this effect are analyzed in Section 5. Section 8 concludes. While the main text focuses on the interaction between an Energy-only market and a Capacity Market, the Online Appendix allows for all combinations with a strategic reserve. Appendix C shows the results of section 4 carry over to non-symmetric demands.

2 Litterature review

The internal energy market, advocating coordination between member states and energy market coupling, is a pivotal instrument to meet the European commission's target in terms of affordability, security, sustainability of power supply (see European Commission (2010)). National markets are now requested to better integrate with neighbors, in order to gain efficiency through increased competition and diversification effects (Creti and Fumagalli (2010), Jamasb and Pollitt (2005)). However, the conflicts between national market designs and the internal energy market have not eased.

The need for an assessment of cross-border effects of capacity remuneration schemes has been repeatedly stressed by many regulators (ACER (2013), CEER (2013), RAP (2013)), market makers (TSOs), participants and institutions (IEA (2014)). Following concerns that " capacity mechanisms may unduly favour particular producers or technologies and that they may create obstacles to trade in electricity across borders", the

European commission carried out an inquiry of eleven mechanisms proposed by member states (European Commission (2016b).

Quite surprisingly, relatively little has been done yet on the research side. Many discussions focus on the short-term (usually positive) cross-border effects of CRMs, while discussions on investment incentives should arguably focus on the long-run effects. Hence, our research is in sharp contrast with conventional wisdom, and previous research based on dynamic arguments (see concerns expressed in Eurelectric (2016)) or focusing on the transition period (Bhagwat et al. (2014), Bhagwat et al. (2017)). In these agent-based models, the authors observe that CRMs yield positive benefits to neighbors, at the expense of local consumers. This contrasts with the results of the present paper that focuses on the long-run equilibrium. While transitory periods are important we believe regulation aimed at promoting long-term investments should be analyzed on the ground of long-run effects. We show that these effects may be unexpectedly damaging, with negative externalities yielded to neighbors of CM. A hint of our results can be found in the empirical literature, that shows cross-border trade may be inefficient when market designs differ (McInerney and Bunn (2013), Viljainen et al. (2013)).

Even though this phenomenon will likely expand very fast in Europe in the next decade, few natural experiments of interconnected markets with different designs are available. Researchers are thus essentially left with two options: simulations and theoretical models. Simulations provide sensible estimates of the magnitude of potential inefficiencies. However, sensitivity to assumptions and the various channels through which the inefficiency arises are often hard to grasp. The present paper is analytical and fills this gap by identifying clearly the effect of interconnections and sharing rules in case of concomitant scarcity.

A notable and inspiring effort to address long-run cross-border inefficiencies by Gore and Meyer (2015) studies the interaction between an energy-only market and a market with a strategic reserve, and between an energy-only market and market with reliability options. They find that unilateral implementation of a capacity mechanism may have negative welfare effects in the neighboring market, which may force it to change its own market design. In addition, Höschle et al. (2016) find that increasing interconnection capacity worsens the situation. The findings of Gore and Meyer (2015) and Höschle et al. (2016) obtained using numerical simulations on stylized markets are fully consistent with our analytical results. Tangerås (2018) also highlights inefficient investments following imperfect market integration.

Close in spirit to our analysis Elberg (2014) finds that system costs are higher in countries in which reserve capacities are procured than in countries in which capacity payments are used. While we focus on an EO/CM interaction we confirm these results and extend to a case with general demand. Also, we show that spillovers are so strong that all costs can be entirely borne by consumers in countries with a SR. Thema (2013), in a report to the EU commission conclude that individual capacity mechanisms can distort the allocation of investment, with investment likely to shift from countries with no CRM to countries with a CRM. Sweco (2014), in a multi-client report finds that total consumer costs are typically higher in countries with a CRM, and reduced in Energy-only market. They highlight that a CRM can reduce the SoS in the neighboring market, thereby leading it to consider implementing a CRM as well. Those reports rely on numerical simulations and qualitative descriptions and lack a formal proof, which we provide in the present paper.

Cross border effects have raised concerns among policy makers –see European Commission (2016b), European Commission (2016a).[3] Simulations show overwhelming evidence in favor of allowing cross-border integration of capacity mechanisms (Cepeda and Finon (2011), Cepeda (2018), Frontier Econonomics (2015), Gore and Meyer (2015)). Several market designs have been proposed so far, but none provides a fully satisfying solution to mitigate undesired cross-border effects. Eurelectric (2015) stresses that market coupling should be preserved and pleads for cross-border participation in CRM. Transmission operators should be given an additional congestion rent based on cross border capacity allocation. It should not be possible to participate with the same capacity in more than one CRM at a time. Frontier Econonomics (2015) recommends that interconnected generators bid directly in the CRM auction and receive the payment for capacity. They would then face a penalty for non-delivery of power during a stress event. Mastropietro et al. (2014) and Mastropietro et al. (2015) suggest a conditional nomination rule for transmission capacity, to be activated when scarcity is declared on both sides of the interconnection. Difficulties to find an adequate mechanism partly explain why both the British and French mechanisms will account of interconnections only in 2019. Consultations show the French system may take account of non-domestic capacities with a probabilistic estimation of their contribution to French Security of Supply, and then sell contribution rights to individual producers (HayaEnergy (2017)). Conversely, the British system allows interconnectors to participate in the capacity market just like generation does with de-rating factors based again on probabilistic assessments. While they may formally allow some cross-border remuneration none of these propositions fixes the

[3]Article 21.1 of the "Proposal for a Regulation of the European Parliament and the Council on the internal market for electricity (recast)" : "Member States shall ensure that foreign capacity capable of providing equivalent technical performance to domestic capacities has the opportunity to participate in the same competitive process as domestic capacity"

phenomenon we highlight in this paper, namely the negative impact on investment in Security of Supply across the border.

3 Model and Benchmark

3.1 The model

The basic elements of this model are similar to Creti and Fabra (2007). We consider three market designs: Energy-Only ("EO"), Capacity Market ("CM") and Strategic Reserve ("SR"). In the paper we will subsequently consider the coupling of these markets two-by-two. There are therefore 6 possible combinations. However, the body of the paper will be focused on the EO/CM coupling, which allows to convey the main insights in a relatively simple manner. Other cases are relegated to Appendix C and the Online Appendix OA.4.

Each market has local inelastic demand l_j, with j standing alternatively for "EO", "SR", "CM", simply denoted l when there is no possible confusion. These demands are stochastic, distributed according to publicly known $F_j(l)$ on $[0, \infty]$. All markets use the same, unique, technology with capacity costs r and variable (fuel) production costs c. Both these costs are expressed in EUR/MWh, r being the annual capacity cost divided by 8760 hours. EO is energy-only, and market CM meets a SoS target through a capacity market, while market SR has a strategic reserve, producing only when the local market is tight (i.e. when price hits the price cap). We are looking for long-run equilibrium capacities, with a known distribution of demand. Hence we assume that there is no construction lead time and no construction cycles. Throughout the paper, we assume that there is free-entry in the generation sector.

Markets are linked by a bidirectional transmission capacity T. T is exogenous, weakly positive and does not induce losses. Transmission may be congested in some states of the world. When markets are isolated, a given SoS standard translates monotonically in a given capacity target. The more stringent the standard, the higher the target. If they have the same SoS target, two isolated market both want to implement a total capacity level $\bar{k}$. Throughout this paper, we assume that $0 < r + c < \bar{P}$, meaning that a finite, strictly positive quantity of capacity will be installed in any market, even absent a capacity remuneration scheme. All agents are risk-neutral.

Since demand is inelastic, regulators impose a price cap on the energy market. Perfect competition implies that price p is at marginal cost c where and when demand is below available operational capacity, and is at the price cap $\bar{P}$ otherwise. For simplicity, we assume that the price cap is set at the Value of Lost Load, which results in consumer surplus per unit of energy consumed being $VoLL - p = \bar{P} - p$. Inelastic demand means there may be some times when all demand cannot be met. In that case, the TSO proceeds to anticipated and proportional load shedding and prices hit $\bar{P}$, the Value of Lost Load.

We will use "Expected Energy Non Served" (EENS, denoted $\mathcal{L}$) as a Security of Supply concept: the smaller $\mathcal{L}$, the higher the SoS. The energy-only market gives rise to an equilibrium capacity k^*, which gives a level of Security of Supply $\mathcal{L}^*$. This EENS derived from market equilibrium may however not be deemed politically satisfying. As Cramton and Stoft (2006) put it, "There is no pure market solution to the resource adequacy problem". Under central planning, policy makers would set an adequacy target that would in turn determine the capacity to be built. In liberalized markets however, market forces give rise to a certain level of EENS which may differ from the policy-marker's target. If the policy-maker finds that $\mathcal{L}^*$ is low enough, the market will stay energy-only. Otherwise he will have to support capacity, either in the form of a capacity market or a strategic reserve.

We assume for simplicity that the EENS target of each market is fixed and exogenous. This means the social planner wants to meet a specific demand coverage target for potentially non-economic reasons. The motivation is therefore not welfare, but Security of Supply itself. In this model, Security of Supply as such does not increase net surplus to consumers. Indeed, the Value of Lost Load being set at the price cap, consumers are indifferent between consuming at a high price, or being curtailed. It is just a target that has to be met: largely exceeding the target does not yield any additional satisfaction to the TSOs or consumers, compared to a situation where the target is just met – set aside the usual welfare increase due to additional demand coverage. A possible rationale for these coverage targets could be that markets may have different VoLLs, potentially above the price cap. In that case, our demand coverage results would be unchanged. This would however complicate net surplus calculations, which we believe would obfuscate the main messages of the paper. Hence we assume that the VOLL is same for all markets.

3.2 Benchmark: Isolated markets

To make market designs easily comparable in this Section, we assume that demands in each market are i.i.d, such that EO, CM, and SR are identical – set aside the market design.

3.2.1 Market EO: Energy only

As discussed, a market stays Energy Only if and only if the market is able to provide –without support– the required level of Security of Supply or more, that is: $\bar{\mathcal{L}} > \mathcal{L}^*$, where the bar denotes the target EENS. Perfect competition means price is c as long as demand is less than capacity, $\bar{P}$ otherwise. Assuming free entry, operational capacity is such that investors just break even. Their profit is:

$$\pi^i_{EO} = 0 = \overbrace{(\bar{P} - c)}^{\text{margin}} \quad \overbrace{(1 - F(k^*))}^{\text{probability of a scarcity}} \quad - \quad \overbrace{r}^{\text{capacity cost}} \tag{1.1}$$

$$\Rightarrow k^* = F^{-1}(1 - \frac{r}{\bar{P} - c}) \tag{1.2}$$

Where subscript i stands for "isolated" market – as opposed to the coupled markets of the next sections. This translates into a SoS level $\mathcal{L}^* = \int_{k^*}^{\infty}(l - k^*)f(l)dl$. The expected hourly net surplus of consumers –which coincides with welfare since we assume free-entry – in EO is:

$$\begin{aligned} W^i_{EO} = W^* = & \overbrace{(\bar{P} - c)}^{\text{value per unit of energy}} \overbrace{\left(\int_0^{k^*} lf(l)dl + (1 - F(k^*))k^*\right)}^{\text{served energy}} - \overbrace{rk^*}^{\text{capacity costs}} \\ = & (\bar{P} - c)\left(\int_0^{k^*} lf(l)dl\right) \end{aligned} \tag{1.3}$$

where we use the fact that no net consumer surplus is generated when load is shed or price is at the cap. The free-entry condition ensures that all welfare is captured by consumers.

3.2.2 Market CM: capacity market

Assume policy makers and/or market designers want to achieve a level of EENS at least as low as $\bar{\mathcal{L}} < \mathcal{L}^*$ which translates in a capacity target $\bar{k}$. There exists a wide variety of capacity remuneration mechanisms which may be technology-neutral or not, centralized or decentralized, volume- or price-based (see European Commission (2016c), page 10 for a summary of existing designs and Adib et al. (2008), Batlle and Rodilla (2010), Cramton and Stoft (2006), De Vries (2007) for critical reviews of those mechanisms). However they all essentially consist in giving an additional payment m^i to some generators in order to make sure there will be enough capacity available at times of high demand. This is the only feature we need in our model, meaning the insights apply to all types of CRMs where operational capacity receives an additional payment –whether this payment is fixed or is the outcome of an auction. Thus we assume that regulator i supports investment with a payment m^i per capacity unit, which is the lowest amount needed in order to meet the adequacy target. Capacity payments are uniform: every MegaWatt of installed capacity receives the same capacity payment. Free entry in market CM means all generators make zero expected profits:

$$\pi^i_{CM} = 0 = m^i + (\bar{P} - c)(1 - F(\bar{k})) - r \tag{1.4}$$

Combining (1.1) and (1.4) yields that $m_i = (\bar{P} - c)(F(\bar{k}) - F(k^*))$ per unit of capacity. We observe that the capacity payment corresponds exactly to the decrease in expected net surplus, which is:

$$\begin{aligned} W^i_{CM} &= (\bar{P} - c)\int_0^{\bar{k}} lf(l)dl - m_i\bar{k} = W^* + \overbrace{(\bar{P} - c)\int_{k^*}^{\bar{k}} lf(l)dl}^{\text{gain from increased SoS}} - \overbrace{m_i\bar{k}}^{\text{addtional capacity payment}} \\ &= W^* - \overbrace{(\bar{P} - c)\left(\int_{k^*}^{\bar{k}} (\bar{k} - l)f(l)dl\right)}^{wefare\ cost\ of\ SoS} \end{aligned} \tag{1.5}$$

Hence by construction of a model without risk-aversion nor any other imperfection, a Capacity Market decreases expected net surplus compared to an Energy Only market. This is not surprising, since the Energy Only design maximizes net surplus by construction. However, understanding the underlying economics is useful. The intuition for this result is that capacity payments are uniform: every MegaWatt of installed capacity receives the same per-unit capacity payment, even though only a fraction of installed capacity is used in (almost) every state of the world. Therefore, the total capacity payments, which is proportional to total installed capacity, exceeds the net surplus generated by additional capacity, which is proportional to capacity actually used. A more detailed analysis of the costs of SoS can be found in Appendix B. On the other hand, SoS is increased as the probability that curtailment occurs is $(1 - F(\bar{k}))$ instead of $(1 - F(k^*))$ in the energy-only market. Similarly, EENS is $\bar{\mathcal{L}} = \mathcal{L}^i(\bar{k}) = \int_{\bar{k}}^1 (l - \bar{k})f(l)dl < \mathcal{L}^* = \int_{k^*}^1 (l - k^*)f(l)dl$.

3.2.3 Market SR: Strategic Reserve

We assume that the strategic reserve is activated only if the price is at the cap, which in our simple environment can be shown to be optimal (see Stoft (2003), Section 2.6.2).

As a consequence the price signal is the same as in market EO, as SR's strategic reserve is activated if and only if the price (weakly) exceeds the price cap. In this paradigm, there will be two types of capacity. First, the traditional capacity is prompted by price signals, as in the EO case. We define it as *operational* capacity denoted k^i_{SR}. Second, a strategic reserve is built so as to bring total capacity to $\bar{k}$.

The price is c if $l \leq k^i_{SR}$. If $l > k^i_{SR}$, the strategic reserve is activated and price is $\bar{P}$. There is curtailment of consumers if and only if $l > \bar{k}$.

The free-entry condition is the same as in the Energy-only case, as the strategic reserve does not modify prices. Hence, operational capacity (i.e. total capacity, less the strategic reserve), remains at k^*:

$$\pi^i_{SR} = 0 = (\bar{P} - c)(1 - F(k^i_{SR})) - r \Rightarrow k^i_{SR} = k^* = F^{-1}(1 - \frac{r}{\bar{P} - c}) \tag{1.6}$$

The TSO needs to procure $k^{SR} = \bar{k} - k^*$ strategic reserves to meet its target. As in the Belgian case, we assume that the TSO covers the fixed costs of strategic reserve producers and reimburses marginal costs when they are active. Therefore the TSO collects $\bar{P} - c$ on each energy unit produced by the SR.[4] This income reduces the direct cost of capacity support. Since producers' profits is equal to zero by construction, the net surplus corresponds to consumer gross surplus minus the market price of electricity, minus the net cost of the strategic reserve:

$$\begin{aligned} W^i_{SR} = & \overbrace{(\bar{P} - c)\int_0^{k^*} lf(l)dl}^{\text{price is low}} + \overbrace{(\bar{P} - \bar{P})\int_{k^*}^{\bar{k}} lf(l)dl + (\bar{P} - \bar{P})(1 - F(\bar{k}))\bar{k}}^{\text{price is high}} \\ & - \Bigg(\overbrace{r(\bar{k} - k^*)}^{\text{SR payment by TSO}} \overbrace{- (\bar{P} - c)\left(\int_{k^*}^{\bar{k}} (l - k^*)f(l)dl + (1 - F(\bar{k}))(\bar{k} - k^*)\right)}^{\text{market profits of SR, captured by TSO}} \Bigg) \end{aligned}$$

The first line corresponds to consumer surplus net of market prices. The second line corresponds to the extra costs associated with capacity provision. Using the free entry

[4] This capture of the rent by the TSO is in accordance with Bhagwat et al. (2014) and most designs where a SR is implemented. One can assume higher payment to active SR plants, up to $\bar{P}$. This would not change the total costs of the SR, as the TSO would have to pay a lesser share of the fixed costs, which in turns benefits consumers. We assume here that the least risk averse agent (i.e. arguably the TSO) gets the uncertain revenues and pays c to producers for each generated unit of electricity

(equation 1.6), the expression simplifies to:

$$\begin{aligned} W^i_{SR} &= W^* - (\bar{P} - c)\left(\int_{k^*}^{\bar{k}} (\bar{k} - l) f(l) dl\right) \\ &= W^i_{CM} \end{aligned}$$

Thus, similarly to Elberg (2014) in our setting with free-entry and risk-neutrality the total social cost is the same with either a capacity market or a strategic reserve. Indeed, given that consumers enjoy the same service in both markets (demand is served until $l \leq \bar{k}$, curtailed afterwards), capacity is $\bar{k}$ in both cases and we must have that $W^i_{SR} = W^i_{CM}$. Given there is free entry and both markets want to achieve the same level of capacity, consumers pay the exact cost of producing electricity, given (an exogenously fixed) total capacity –and nothing else. That is, with either design they need to pay for capacity fixed costs, plus marginal costs of production.[5] In the strategic reserve design, high expected prices in the energy market decrease the upfront costs of reserve capacity. In the capacity markets design, upfront costs are higher as high wholesale prices are highly infrequent, and therefore investors need to be largely incentivized. Consumers recover this high cost through lower energy prices.

The rest of the paper focuses on the EO/CM interaction. SR/CM and SR/EO cases are treated in the Online Appendices OA.1 to OA.4.

4 Interconnected EO/CM markets – symmetric markets

Consider an energy only market EO, interconnected with a market with capacity market CM. In this section, we assume that demands in EO and CM are perfectly correlated. That is, in all states of the world $l_{EO} = l_{CM} = l$. This assumption is relaxed in Appendix C which extends the analysis to independent and identically distributed demands. The fully general case of non-identically distributed demands is left for future research.

4.1 Sharing rule

Before proceeding to the analysis of cross-border effects of CRMs, a definition the sharing rule in case of concomitant scarcity is in order. Throughout the paper we will focus on two polar cases that we believe describe the two extremes between which existing regulatory environments lie.

[5]it is important to note that we assumed risk neutrality. If agents are risk-averse, those conclusions may not hold

In a first paradigm, consistent with most network codes (see Mastropietro et al. (2014)), TSOs will strive to ensure stability on their own network and avoid curtailing their own consumers. Thus, they may reduce export capacity at times of scarcity in order to meet local demand. We define this as the "domestic priority" paradigm:

Rule 1. *According the "domestic priority" sharing rule, TSOs are allowed to reduce export capacity to maintain the SoS in their control area.*

This paradigm is the historic one, and still prevails since national network codes allow TSOs to reduce export capacity to ensure that full demand coverage is maintained in their control area (see Mastropietro et al. (2014)). However initiatives to jointly deal with scarcity events do exist. In Europe, the first Regional Security Coordination Initiatives and the establishment of Coreso and TSC in 2008 have allowed TSOs to coordinate operations. Intentions to further coordinate on issues of Security of Supply have been declared BMWi (2015)) and practical options for implementation are analyzed in FTI-Compass Lexecon energy (2016). While in their infancy, these initiatives indicate a political will to jointly manage scarcity.

In a second paradigm, more consistent with the Security of Supply directive (2005)[6] and the spirit of the European Internal Energy Market, TSOs would coordinate so that the magnitude of the curtailment is the same on both sides of the border. This rather extreme paradigm implies full solidarity between markets.

Rule 2. *According to the "cross-border solidarity" rule TSOs cooperate such that the magnitude of load shedding is same in each consumer area.*

Of course, there might be other allocation rules (energy allocated pro-rata of capacity, pro-rata of local demand...), but we believe those two paradigms correspond to two extreme situations and adding intermediary allocation rules would add little insight.

As will be shown in Section 5.1, the "cross-border solidarity" paradigm leads to an irrelevance result for unilaterally implemented capacity markets. If markets ex-ante agree and commit to arrange cross-border flows so that both markets are equally curtailed, then the geographical location of capacity does not matter as energy will be dispatched according to where demand is, and not where supply is. Furthermore, we show that in the long-run a capacity market does not *create* capacity overall, but merely displaces it from the EO market to the CM market. For this reason, in this paradigm there is no point implementing a CRM. It is therefore likely that regulators currently implementing

[6] Security of Supply Directive (2005/89/EC), states that "Member States shall not discriminate between cross-border contracts and national contracts".

a CRM will try to manage their exports such that the CRM does improve their own markets' SoS.

Thus, in the present section we investigate the case where TSOs have a preference for consumers in their control area (rule 1) i.e., they can reduce export capacity in case of system stress (domestic preference), but do not control import capacity.[7] These assumptions reflect current national regulations. Online Appendix OA.6 shows that adding some small cross-border transaction costs or transmission losses allows to relax the domestic preference assumption. The effects of Rule 2 will be analysed in Section 5.1.

4.2 Transmission is never binding

Assume first that the transmission is so large that it never binds. The amount of electricity to be transmitted when load is at l is $(min\{\bar{k} - l, l - k_{EO}\})^+$ which reaches a maximum value $\frac{\bar{k}-k_{EO}}{2}$ when $l = \frac{\bar{k}+k_{EO}}{2}$. Hence, transmission is never binding if and only if $T > \frac{\bar{k}-k_{EO}}{2}$. As in the isolated case, price is at marginal cost c as long as total demand is less than total capacity. When total demand demand exceeds total capacity, price jumps at $\bar{P}$. Indeed, as soon as there is some curtailment in one of the two markets, prices hit the cap: if price were lower in the market with excess capacity, a generator would sell in the tight market instead of the market with excess capacity.[8] Furthermore, TSOs are allowed to reduce exports only if domestic demand falls short of supply, which translates in prices hitting the cap. Their intervention is therefore conditioned on prices being high, which preserves market signals. The possible states of Nature can be summarized as follows:

[7] The SoS directive explicitly stresses that TSOs shall not discriminate between national and foreign generation

[8] Alternatively, some traders would use the transmission line and arbitrage the price difference

Demand	p_{EO}	p_{CM}	Exports from CM to EO	Profits made by CM producers in EO
$l \leq k_{EO}$	c	c	0	0
$k_{EO} < l \leq \frac{\bar{k}+k_{EO}}{2}$	c	c	$l - k_{EO}$	0
$\frac{\bar{k}+k_{EO}}{2} < l \leq \bar{k}$	$\bar{P}$	$\bar{P}$	$\bar{k} - l$	$(\bar{P} - c)(\bar{k} - l)$
$\bar{k} < l$	$\bar{P}$	$\bar{P}$	0	0

Table 1.2: States of Nature – correlated demand: $l_{EO} = l_{CM} = l$, transmission is not binding. Perfect competition imposes that price is at marginal cost as long as there is spare capacity ($2l \leq \bar{k} + k_{EO}$), and hits $\bar{P}$ otherwise.

Demand coverage in CM is unaffected by EO's capacity level, as CM's consumers receives priority in case of scarcity, and EO's capacity is less than CM's by assumption. Therefore with correlated loads if CM is tight, *a fortiori* EO is tight and can't export. This translates in $k_{CM} = \bar{k}$. Free-entry conditions in what is effectively a single market are:

$$Market\ CM: \quad r = m + (\bar{P} - c)\left(1 - F\left(\frac{\bar{k} + k_{EO}}{2}\right)\right) \tag{1.7}$$

$$Market\ EO: \quad r = (\bar{P} - c)\left(1 - F\left(\frac{\bar{k} + k_{EO}}{2}\right)\right) \tag{1.8}$$

It follows immediately from (1.7) and (1.8) that $m = 0$: as long as there is a strictly positive amount of capacity in market EO, CM pays only a negligible upfront payment m to attract investments. Total capacity is determined by (1.8):

$$\frac{\bar{k} + k_{EO}}{2} = F^{-1}\left(1 - \frac{r}{\bar{P} - c}\right) = k^* \tag{1.9}$$

$$\Rightarrow k_{EO} + \bar{k} = 2k^* \tag{1.10}$$

This means total capacity stays at the (regionally) optimal level, whatever the capacity target in CM , provided that capacity in EO remains strictly positive.

Inserting this result in Table 1.2, we observe that prices for either consumers in EO or CM are unchanged compared to the case with no CRM: prices are at c as long as $l < k^*$, at $\bar{P}$ otherwise. This insight contrasts sharply with those brought about by a short-term analysis where consumers in EO would benefit from the additional capacity in CM through lower price and "capacity spillover". In the long run, there is in reality no additional capacity overall –only its distribution among EO and CM is modified by the CRM.

Also, it is useful to note at this stage that both Table 1.2 and equation (1.10) hold even if the Value of Lost Load were set above the price cap in either of both markets: prices and in turn investment and Security of Supply would be unchanged compared to the present analysis.

Net surplus in the market with a capacity market

Net surplus in market CM, given that $k_{CM} = \bar{k}$ and $k_{EO} = 2k^* - \bar{k}$ is:

$$\begin{aligned} W_{CM}(\bar{k}, 2k^* - \bar{k}) &= \overbrace{(\bar{P} - c)\int_0^{k^*} lf(l)dl}^{\text{price is low}} + \overbrace{(\bar{P} - \bar{P})\left(\int_{k^*}^{\bar{k}} lf(l)dl + \left(1 - F(\bar{k})\right)\bar{k}\right)}^{\text{price is high}} - m * \bar{k} \\ &= (\bar{P} - c)\left(\int_0^{k^*} lf(l)dl\right) \\ &= W^* = W^i_{CM} + (\bar{P} - c)\left(\int_{k^*}^{\bar{k}} (\bar{k} - l)f(l)dl\right) \end{aligned} \tag{1.11}$$

For all capacity targets $\bar{k} > k^*$, CM consumers enjoy decreased costs compared to the isolated case. Interestingly the cost reduction (equivalently, the incremental net surplus, since demand coverage is unchanged compared with the isolated case), is exactly the cost of the support scheme when markets are isolated (either with SR or CM). Thanks to the interconnection with its energy-only neighbor, CM meets its SoS target at zero cost!

Net surplus in the energy-only market

In terms of net surplus, market EO is indifferent between curtailing consumers and getting high-priced imports. One can assume that CM exports at a price just below $\bar{P}$ so that EO does import from CM (and is just indifferent between importing and curtailing). Recall that we have that $k_{CM} + k_{EO} = 2k^*$: capacity in EO decreases such that total capacity remains at the optimal level (according to the energy-only market equilibrium level).

$$W_{EO} =(\bar{P}-c)\left(\int_0^{k^*} lf(l)dl\right)+(\bar{P}-\bar{P})\left(\int_{k^*}^{\bar{k}}(2k^*-l_{CM})f(l)dl+(1-F(\bar{k}))(2k^*-\bar{k})\right)$$
$$=W^* \tag{1.12}$$

Thus, net surplus in EO is unchanged following the implementation of a CM in a neighboring country. When transmission is non-binding, the analysis is summarized in the following proposition:

Proposition 1.1. *With perfectly correlated demands and non-binding transmission capacity, a market with a capacity market increases its Security of Supply at no cost. Overall Security of Supply remains unchanged as long as capacity in the energy-only market remains strictly positive. The expected net surplus is unchanged in the EO market, but SoS decreases by the same amount as it increases in the CM market.*

Proof. As proven above, EO is indifferent to CM's decision to implement a capacity market, from a welfare point of view. *A fortiori* EO is also indifferent to $\bar{k}$. The expected curtailment was $\mathcal{L}^* = \int_{k^*}^1 (l-k^*)f(l)dl$ when CM had no binding EENS target and $k_{EO} = k^*$. However, when CM implements a strictly positive payment, EENS in EO becomes:

$$\mathcal{L}_{EO}^{connected} = \int_{k^*}^{\bar{k}}(2l-2k^*)f(l)dl + \int_{\bar{k}}^{\infty}(l-(2k^*-\bar{k}))f(l)dl$$
$$= \mathcal{L}^* + \int_{k^*}^{\bar{k}}(l-k^*)f(l)dl + (1-F(\bar{k}))(\bar{k}-k^*) > \mathcal{L}^*$$

We observe that the EENS loss in EO, $\mathcal{L}^* - \mathcal{L}_{EO}^{connected}$ is precisely the incremental demand coverage in CM. □

Proposition 1 proves that, in the long-run, implementing a capacity mechanism in one market harms consumers in its neighboring market, by reducing the latter's Security of Supply. This result stands in sharp contrast with the commonly held wisdom that consumers will free-ride on their neighbors' capacity payments. Key to this result is the difference between short- and long-run impacts, as illustrated on Figure 1. The short-run perspective takes generation capacity in the market with no intervention as given, while long-run considers generation capacity is at its long-run equilibrium, derived from free-entry conditions.

Isolated markets are presented on the left panel of Figure 1.1. Installed capacity are $\bar{k}$ in CM and k^* in EO. Consider now that both markets are connected. In the short-run (middle panel), EO's consumers are indeed better off, as CM producers export into EO when demand exceeds EO's capacity k^* yet is lower than the target capacity $\bar{k}$. EO's consumers free-ride on CM's consumers capacity payments in the short-run.

This free-riding is short-lived, however. EO's producers are pushed out of the market by their subsidized competitors from CM. In the long-run equilibrium, expected net surplus is equal and optimal in both markets, and SoS is reduced in EO. By connecting with EO, CM increases its net surplus at the cost of a reduction in EO's Security of Supply.

A similar analysis could be presented starting from two interconnected EO markets, and implementing a capacity mechanism in one of them. Aggregate expected net surplus and installed capacity are unchanged. Net surplus in each market is also unchanged. However, implementing a capacity mechanism in one market reduces Security of Supply in the other one compared to the EO case. By implementing a capacity mechanism, CM increases its SoS at the expense of EO's SoS.

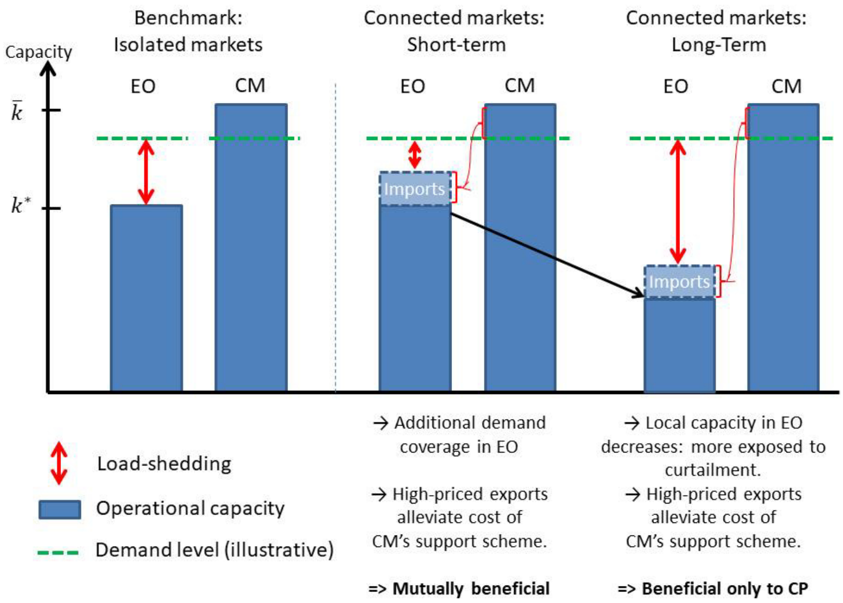


Figure 1.1: EO free-rides CM's capacity in the short term, but in the long run its local capacity decreases, together with its SoS level

Note that in a rather extreme case, if $\bar{k}$ is so large that k_{EO} falls to 0 (i.e. by Equation

1.10, target capacity in CM is weakly more than twice the equilibrium level); market EO is merely used as a buffer to market CM's excess capacity, and has a very low SoS level. However, if $\bar{k} \gg 2k^*$, it may be the case that the energy-only market is better off when it is connected with CM than when it isn't: if capacity in CM is so large that EO's SoS target is met even with zero local capacity, then EO's welfare is improved. Only in this extreme case one can say that EO "free-rides" CM's capacity in the long run. This case seems however highly unrealistic if the markets are sufficiently big, as the EO market becomes totally dependent on his neighbor. Therefore, we focus on the case $\bar{k} < 2k^*$ throughout the paper.

4.3 Transmission is binding

When transmission is binding (i.e. $T \leq \frac{\bar{k}-k_{EO}}{2}$), the possible states of Nature can be summarized as follows:

Demand	p_{EO}	p_{CM}	Exports from CM to EO	Profits made by CM in EO	Congestion rent
$l \leq k_{EO}$	c	c	0	0	0
$k_{EO} < l \leq k_{EO} + T$	c	c	$l - k_{EO}$	0	0
$k_{EO} + T < l \leq \bar{k} - T$	$\bar{P}$	c	T	0	$(\bar{P} - c)T$
$\bar{k} - T < l \leq \bar{k}$	$\bar{P}$	$\bar{P}$	$\bar{k} - l$	$(\bar{P}-c)(\bar{k}-l)$	0
$\bar{k} < l$	$\bar{P}$	$\bar{P}$	0	0	0

Table 1.3: States of Nature – correlated demand: $l_{EO} = l_{CM} = l$, transmission is binding

Compared to the states of nature when transmission is not binding (table 1.2), a new type of state of the world emerges when transmission binds (line 4 in Table 1.3). When $k_{EO} + T < l \leq \bar{k} - T$, limited transmission capacity prevents demand in the EO market to be satisfied. This mechanically results in prices hitting the cap and load shedding to occur in EO. However CP demand plus exports are still lower than installed capacity, hence CP demand is fully served and prices are maintained at c.

Each market allows entry, meaning the zero-profit condition pins down installed capacities. Denoting by superscript c the congested case:

$$\begin{aligned}\pi_{EO} = 0 = (\bar{P}-c)[1-F(k^c_{EO}+T)] - r \\ \Rightarrow k^c_{EO} = F^{-1}(1-\frac{r}{\bar{P}-c}) - T = k^* - T\end{aligned} \tag{1.13}$$

Note that $k^c_{EO} = k^* - T > k^* - \frac{\bar{k}-k_{EO}}{2} = 2k^* - \bar{k} = k_{EO}$. Hence we have that $k_{EO} < k^c_{EO} < k^i_{EO}$: while still negative, the effect of a neighboring CM is mitigated by the limitation of transmission capacity.

Again, demand coverage in CM is unaffected by the connection with EO, as CM's consumers gets priority over CM's generation in case of scarcity, and EO's capacity is less than CM's. Free-entry in market CM yields:

$$r = m^c + (\bar{P}-c)\left(1-F\left(\bar{k}-T\right)\right) \tag{1.14}$$

$$\Rightarrow 0 < m^c = (\bar{P}-c)\left(F\left(\bar{k}-T\right) - F\left(k^*\right)\right) \leq (\bar{P}-c)\left(F\left(\bar{k}\right) - F\left(k^*\right)\right) = m^i \tag{1.15}$$

The capacity payment is now positive (unlike in the no-congestion case), but less than the payment in isolation: unlike in the no-congestion case, capacity in CM is no longer a perfect substitute to capacity in EO. Therefore, there will indeed be a strictly positive capacity payment m^c.

CM's gross consumer surplus is unchanged compared to the isolated case. Thus, the cost reduction translates in an equivalent increase in welfare. When congestion is binding a congestion rent arises. We assume the TSO in CM owns a share $\alpha \in [0,1]$ of the transmission rights, and EO owns the remaining $(1-\alpha)$. This revenue would be transferred to consumers in the form of reduced regulated base.[9] Similar calculations as in (1.11) yield:

$$W^c_{CM} = W^i_{CM} + (\bar{P}-c)\Big(\alpha \overbrace{T(F(\bar{k}-T) - F(k^i_{EO}))}^{congestion\ rent} + \overbrace{\int_{\bar{k}-T}^{\bar{k}} (\bar{k}-l)f(l))dl}^{\substack{export\ idle\ capacity\ to\ CM \to EO \\ absent\ congestion}}\Big)$$

W_{CM} is increasing in T. This means that when TSOs can reduce export capacity at times of scarcity, the TSO in CM nonetheless benefit from high transmission capacity, as it allows more shifting of capacity installations from the EO to CM market. Again, in

[9] Alternatively, if the transmission is privately owned α would correspond to the financial transmission rights sold to operators in CM. In expectation and with a perfectly competitive markets for financial transmission rights this would not modify the profits made by operators.

terms of welfare, market EO is indifferent between curtailing consumers and getting high price imports. Using (1.13), we can show that market EO gets an incremental value:

$$
\begin{aligned}
W_{EO} - W^* = &T\Big(\overbrace{r}^{\substack{\textit{Less capacity}\\ \textit{is needed}}} - \overbrace{(\bar{P} - c)(1 - F(k^i_{EO}))}^{\substack{\textit{Incremental high priced imports}\\ \textit{or curtailment}\\ \textit{(locally available if EO were isolated)}}} \Big) \\
&+ (1-\alpha)\overbrace{(\bar{P} - c)T(F(\bar{k} - T) - F(k^* + T))}^{\textit{congestion rent}}
\end{aligned}
$$

By free-entry in market EO, the first term cancels out:

$$W_{EO} - W^* = (1-\alpha)(\bar{P} - c)T(F(\bar{k} - T) - F(k^*)) \geq 0$$

In short, market EO builds T less capacity and purchases power from CM when $k^* < l < \bar{k}$. CM's welfare is augmented as in some states of the world, some otherwise idle capacity can export to EO at high prices. Disregarding congestion rents, or assuming CM owns it, EO's welfare is unchanged as it builds less capacity, but needs to buy more power from CM, and these two effects cancel out. If EO owns some share of transmission rights, his welfare is increased. It is therefore (weakly) mutually beneficial to keep the markets interconnected. In the reasonable case where the exporters own the transmission rights (whether it is the exporting TSO or the exporting producers) and get the congestion rent ($\alpha = 1$) EO sees no welfare increase.

Congestion rents, or a compensation payment from CM may constitute a consolation prize for the loss in Security of Supply endured by EO: without interconnection, the expected curtailment is $\mathcal{L}^* = \int_{k^*}^1 (l - k^*)f(l)dl$. With interconnection it becomes:

$$
\begin{aligned}
\mathcal{L}_{EO} &= \int_{k^*}^{\bar{k}-T} (l - (k^c_{EO} + T))f(l)dl + \int_{\bar{k}-T}^{\bar{k}} (2l - (k_{EO} + \bar{k}))f(l)dl + \int_{\bar{k}}^{\infty} (l - k^c_{EO})f(l)dl \\
&= \mathcal{L}^* + \int_{\bar{k}-T}^{\bar{k}} (l - (\bar{k} - T))f(l)dl + (1 - F(\bar{k}))T > \mathcal{L}^*
\end{aligned}
$$

Thus, proposition 1.1 can be extended to the case when transmission is binding:

Proposition 1.2. *If the transmission line is sometimes congested, and depending on the allocation of transmission rights, albeit losing ground from the point of view of Security of Supply, an energy-only market connected to a market with capacity market can get additional revenues through congestion rents, translating in an increase in net surplus.*

Proof. Follows from previous developments □

Note also that jurisdictions implementing a capacity market have a strong incentive to reduce export capacity at times of scarcity, as it increases their SoS at a small cost. This however decreases the neighbors' SoS. If they secure the right to reduce export capacity, they will however benefit from a large physical transmission capacity that enables them to enjoy a strong business stealing effect (see equation 1.13).

Importantly, we can show that the results of this Section carry over to a case when demand would not be correlated (see Appendix C). Note however that propositions 1.1 and 1.2 are true only as long as EO stays energy-only. Following these strong effects EO may react by changing his own design. In the following section we explore some natural reaction strategies.

5 What may the Energy-Only market do to protect its Security of Supply?

We have shown that an Energy-Only market will likely be prejudiced if its neighbor unilaterally implements a Capacity Market. What are the possible responses of the EO regulator or TSO? We first explore in Section 5.1 the consequences of a joint management of curtailment ("cross border solidarity", defined in Section 4.1). We then show in Section 5.2 that cross-border procurement of capacity does not solve any of the issues we described earlier. Failing international coordination, we then explore the case when EO implements a SR or a CM (Section 5.3). Finally we show in Section 5.4 that providing a small payment for capacity in EO can be welfare-improving.

5.1 The "cross-border solidarity" sharing rule

Assume that TSOs surrender their preference for local consumers, and they agree on the "cross-border solidarity" paradigm (see rule 2 in section 4.1). This means they arrange flows so that the magnitude of curtailment is the same in both market at all times: for example if total demand exceeds total capacity by 2 MW, each market will curtail 1MW, independent of where capacity is located.

5.1.1 Non-binding transmission

If transmission is not binding, the free-entry conditions (1.7) and (1.8) still apply. Indeed, in our model, prices and thus investment incentives are independent from the sharing rule: prices hit the price cap if and only if the (integrated) market is tight. Given that there is no creation of capacity, demand is unchanged and the CM is costless since it follows from (1.7) and (1.8) that $m = 0$.

However, in this simple model unilaterally implemented CMs are also useless: by definition of the sharing rule, the EENS will be the same in both countries. In that case, with non-binding transmission and with solidarity between markets, CMs are irrelevant unless they are jointly implemented. Online Appendices OA.1 to OA.5 show that strategic reserves have a positive effect, but some positive spillovers to neighbors may not be rewarded adequately.

5.1.2 Binding transmission

As in Section 4.3, matters get more complicated when transmission is binding. TSOs can ensure that demand is equally curtailed only if the transmission capacity allows it. Again, the free-entry conditions (1.13) to (1.14) still hold. As in the "domestic preference" case (see Appendix C.2), the capacity payment is positive and there is creation of capacity. Thus, the market with a CRM enjoys additional demand coverage.

When demands are symmetric, and markets commit to solidarity, the SoS in the Energy-Only market is unaltered: we have seen that capacity in the no-CRM market reaches $k^* - T$. When demand exceeds local capacity, the Energy-Only market imports up to T. Even when both markets are tight, the market with a Capacity Market continues to send T to the Energy-Only market (since $l - (\bar{k} - T) > l - (k_{EO} + T)$ by definition of the transmission capacity being binding) and the Energy-Only market still enjoys $k_{EO} + T = k^*$ available capacity at all times, as if there were no CRM at all. Thus, any additional demand coverage will occur in the market with a CRM. How much capacity is created has no impact on the neighboring market, as the transmission line is congested anyway. Thus, when transmission is binding, the "cross-border solidarity" paradigm allows CRMs to be both relevant *and* have no cross-border welfare nor SoS impact. However, it requires a large displacement of capacity from the market with no-CRM to the market with a CRM.

When demands are symmetric, the impact of a unilaterally-implemented Capacity Market to reach a given level of domestic demand coverage is summarized in Table 1.4. It distinguishes the cases when the transmission is binding or not, and which of the sharing rule prevails. Appendix C shows that these results carry over to non-symmetric demand. As a notable exception, if demands are not symmetric, rule 2 (solidarity) prevails but transmission is binding, then SoS in the Energy-Only market may decrease (see figure

1.2).

rule / transmission	Domestic preference	Cross-border solidarity
Non-binding	No creation of capacity EO's SoS decreases	No creation of capacity No impact on EO's SoS
Binding	Creation of capacity EO's SoS decreases	Creation of capacity No impact on EO's SoS

Table 1.4: Impact of a unilateral implementation of a Capacity Market on total regional capacity and a neighbour's consumer expected net surplus

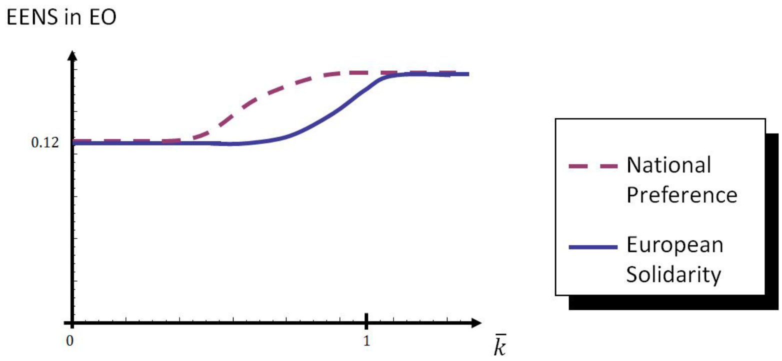


Figure 1.2: EENS in an Energy-Only market, as a function of its neighbor's capacity target $\bar{k}$. The dotted line shows EENS when TSOs follow the domestic preference paradigm, the solid line shows EENS when TSOs commit to cross-border solidarity. $T = 0.1$, $\bar{P} = 1200$, $c = 100$, $r = 500$, demand is uniformly distributed and i.i.d.

This leads to the following conclusions:

- Whether transmission is binding or not, the "cross-border solidarity" rule mitigates the negative cross-border effects on Security of Supply.
- If a regional TSO manages to enforce cross-border solidarity, a unilateral CM is useless unless transmission is binding. Local TSOs willing to implement a CRM will therefore have an increased incentive to under-size transmission capacities, in order to isolate their markets as much as possible.

5.2 Cross-border contractual agreements

In the present paper we assumed that a given TSO could sign a contract only with plants located in its own jurisdiction. However regulators have long been concerned of a potential conflict between national schemes and the European Electricity Target Model which aims at promoting competition by opening national markets to non-domestic participants ACER (2011). This led the European commission to require CRMs to allow for cross-border participation (see European Commission (2015), European Commission (2016a)).

If an integrated approach to CRMs is not feasible, a variety of options exist so as to take account of non-domestic contribution to local adequacy (see Linklaters (2014) for reviews of such options). When signed with a non-domestic generator, a contract for capacity requires that the non-domestic generator must generate when the local system is tight and that this generation can effectively be transmitted to the local market. The payment will be proportional to the ability of the non-domestic generator to contribute to adequacy in the local market.[10] At times of concomitant scarcity this means production needs to be shipped to the market with a contract –potentially depriving consumers located closer to the plant. This case is formally equivalent to the "domestic priority" rule – the only difference being that the contracted plants are geographically located in the foreign country. During scarcity events, production from the plant is conveyed through the transmission line instead of being consumed locally. Thus, despite the fact that power plants may geographically remain in the foreign country, welfare and SoS implications are same as found in Sections 4.

Another way to take account of and remunerate foreign contribution to local SoS would be to allow the participation of interconnectors in local CRMs. Once appropriate de-rating factors are established, interconnectors could bid in the same auctions as traditional generation. In that case, all the free-entry equations (1.7, 1.8, 1.13, 1.14) and the sharing rules and flows (tables 1.2 and 1.3) are maintained, meaning all the previous insights would carry over. To make the topic interesting one would then need to endogenize transmission capacity, which is beyond the scope of the present paper that assumes that transmission capacity is exogenous. The question of investment in interconnectors and the effects of their participation in foreign CRMs on local investment in generation is left for future research. The interested reader is referred to Van den Bergh

[10] We abstain here from discussing the significant challenges borne by the computation of such – even short term – contributions as it goes much beyond the scope of this paper. The interested reader is referred to the Bristish National Grid (2016) and French RTE (2016) methodologies or Antweiler (2016) for further information.

et al. (2018) for interesting insights on the issue of transmission capacity allocation for reserve markets.

5.3 Implementing a CRM as well: CM or SR?

Assume that CM's capacity market reduced EO's Security of Supply below what the market designer in EO deems acceptable: $\mathcal{L}_{EO}(\bar{k}, k_{EO}(\bar{k})) > \bar{\mathcal{L}}_{EO}$. Then, the market designer in EO may opt for a CRM as well. The question is, should it implement it in the form of a strategic reserve, or a capacity market?

Assume EO wants to increase its SoS by a given increment. From the point of view of SoS, whether EO increases local capacity by means of a SR of a CM does not matter: local demand has priority over local generation whether this generation capacity is operational or strategic. Demands being correlated any addition in capacity in EO will have no impact on the neighbor's target, as long as $k_{EO} < \bar{k}$. We can thus assume that the desired SoS increase translates in a capacity increment of $\delta > 0$ that does not modify the neighbors' target. Capacity installed in EO will then be with $k_{EO} = 2k^* - \bar{k} + \delta$. While the EO market effectively implements a support for capacity, we keep naming it "EO" to distinguish it from the "CM" neighbor who took the initiative to implement some support in the first place.

First, we calculate the cost in terms of net surplus of the implementation of a SR. The SR being activated only when prices are at the cap (and thus at the VOLL), consumers receive no net benefits from the SR. The welfare variation corresponds solely to net costs of the SR for the TSO.

$$\Delta W_{EO \to SR} = (\bar{P} - c)\Bigg[\overbrace{\int_{k^*}^{k^*+\frac{\delta}{2}} 2(l - k^*)f(l)dl}^{\substack{\text{extra demand coverage} \\ \text{when CM limits exports}}} + \overbrace{\delta\left(1 - F\left(k^* + \frac{\delta}{2}\right)\right)}^{\substack{\text{extra demand coverage} \\ \text{when CM exports are 0}}} \Bigg] - r\delta$$

using the free-entry condition (1.7) it simplifies to:

$$= -2(\bar{P} - c)\int_{k^*}^{k^*+\frac{\delta}{2}} (k^* + \frac{\delta}{2} - l)f(l)dl \qquad (1.16)$$

Now we calculate the costs in terms of net surplus of providing a payment for capacity. On the cost side, EO will have to pay a capacity payment to all capacity located in his consumer area. The payment will be set by the free entry conditions (equivalent to 1.7

and 1.8) :

$$Market\ EO: \quad r = m_{EO} + (\bar{P} - c)\left(1 - F\left(\frac{\bar{k} + k_{EO}}{2}\right)\right) \tag{1.17}$$

$$Market\ CM: \quad r = m_{CM} + (\bar{P} - c)\left(1 - F\left(\frac{\bar{k} + k_{EO}}{2}\right)\right) \tag{1.18}$$

We thus have that $m_{EO} = m_{CM} = (\bar{P} - c)\left(F\left(\frac{\bar{k}+k_{EO}}{2}\right) - F(k^*)\right)$. Consumers will also enjoy cheap energy when the system is loose $l \in [k^*, k^* + \frac{\delta}{2}]$. The decrease in net surplus is therefore:

$$\begin{aligned}\Delta W_{EO\to CM} &= -(\bar{P} - c)\left[(2k^* - \bar{k} + \delta)\left(F\left(k^* + \frac{\delta}{2}\right) - F(k^*)\right) - \int_{k^*}^{k^*+\frac{\delta}{2}} l f(l) dl\right] \\ &= -(\bar{P} - c)\int_{k^*}^{k^*+\frac{\delta}{2}} (2k^* - \bar{k} + \delta - l) f(l) dl \end{aligned} \tag{1.19}$$

We notice that :

$$\Delta W_{EO\to SR} = \Delta W_{eo\to cm} - \int_{k^*}^{k^*+\frac{\delta}{2}} (\bar{k} - l) f(l) dl$$

The decrease in net surplus is thus greater when EO implements a SR than a CM. Further if EO wants to match the SoS of his neighbors (thus setting $\delta = 2(\bar{k} - k^*)$ so as to avail itself of $\bar{k}$ local capacity), we can show that $\Delta W_{eo\to sr} = 2\Delta W_{eo\to cm}$. This means SR is twice more expensive than CM. To maintain its SoS, an Energy-Only market should therefore implement a capacity market instead of a strategic reserve. Indeed we saw in Section 4 that a Capacity Market destroys less net domestic surplus if it is connected to a neighbor – at the expense of the Security of Supply of the non-domestic market. A Strategic Reserve does not generate such negative externalities to neighbors, and we show in Online Appendix OA.3 that the costs of the SR is same whether the market is interconnected or not. It results that the best reply of an Energy Only market to a neighbor's implementation of a Capacity Market is to also implement a Capacity Market.

5.4 EO switches to a capacity market: here comes the free-riding

We saw in the previous section that if EO has to implement some capacity support, he should do it through a capacity market, and not a strategic reserve. In this section, we will see that it might actually be *profitable* for EO to increase slightly its capacity through a payment, even absent any consideration on SoS.

Assume as in previous section that "EO" now has a target $\bar{k}_{EO} = 2k^* - \bar{k} + \delta$ with $\delta > 0$, which he decides to meet with a capacity payment m_{EO}. Implications for net surplus are described by equation (1.19). Note first that this formula is consistent with our previous findings. If the EO market does not try to maintain any target (i.e. $\delta = 0$), then $W_{EO}(\bar{k}, \delta = 0) = W^*$. If the EO market decides to implement the same reliability level as market CM (i.e. $\delta = 2(\bar{k} - k^*)$), both markets become perfectly symmetric, and there are no longer any gains or losses from trade: $W_{EO}(\bar{k}, 2(\bar{k} - k^*)) = W_{CM}(\bar{k}, 2(\bar{k} - k^*)) = W^i_{CM}(\bar{k}) < W^*$. However some intermediate target might increase net surplus in EO. Differentiating equation (1.19) with respect to δ :

$$\frac{\partial W_{EO}}{\partial \delta}(\bar{k}, \delta) = (\bar{P} - c)\left[\frac{1}{2}\left(\bar{k} - k^* - \frac{\delta}{2}\right) f\left(\bar{k} + \frac{\delta}{2}\right) - \left(F\left(\bar{k} + \frac{\delta}{2}\right) - F(k^*)\right)\right]$$

Observe that $\frac{\partial W_{EO}}{\partial \delta}(\bar{k}, \delta = 0) = (\bar{P} - c)\frac{\bar{k} - k^*}{2} f\left(\bar{k} + \frac{\delta}{2}\right) \geq 0$, meaning that increasing capacity slightly through a capacity market increases net surplus compared to the "no regulatory reaction" case. The capacity in EO that maximizes net surplus, even absent SoS concerns lies in $]2k^* - \bar{k}, \bar{k}[$. Indeed, EO does not take into account the negative externality it yields to the CM market, in the form of increased capacity payment not only in EO, but also in CM. Therefore, there may be over-investment in capacity overall.

6 Conclusion

We start with a benchmark situation where support schemes, implemented in markets without neighbors, are equivalent whether it takes the form of a capacity market or a strategic reserve. Then, we observe the cross-border impact of CRMs in the long-run. For a capacity market to be effective, we show that one needs to have either limited transmission capacity, or that TSOs can reduce export capacity. Both solutions seem to be in direct contradiction with the spirit of the Internal Energy Market. If an electricity market unilaterally implements a capacity market, operational capacity in a neighboring Energy-only or Energy-only+Strategic Reserve market shrinks. If TSOs are allowed to reduce export capacity, those neighbors will be prejudiced and may want to implement a (costly) capacity market as well, in order to maintain their Security of Supply standard. Hence, capacity markets may spread in Europe because of their negative cross-border externalities on investment. A rather surprising result is that, given the SoS-decreasing effect observed in Section 4 a decision maker willing to implement a CRM might need to *compensate* the neighboring EO markets for the SoS loss it endures. A strategic reserve has no negative cross-border externalities on net surplus, but neighbors enjoy incremental SoS for free. Only in the case of a capacity support in the form of a strategic reserve, can one say that an energy-only neighbor "free-rides" on neighboring CRM in the long-run. Our conclusions urge for the harmonization of capacity remuneration schemes across Europe.

To gain realism a number of assumptions may be relaxed. Imperfect foresight of demand distribution, risk aversion, construction lead times, business cycles are assumed away but may need to be integrated so as to better represent the initial motivation of the policy-maker. The cross-border costs of such CRMs could be balanced against these benefits. Then, this work can be extended in at least two obvious directions. First, an empirical analysis could be carried out to understand the magnitude of the cross-border investment effect, and the extent to which a non-domestic market is affected by neighboring supported capacity. This will allow to estimate which market players should participate in CRMs and whether some compensation to neighbors should be considered. Second, transmission capacity could be endogenized. Taking into account the effects of transmission on capacity equilibrium in the long-run, optimal and equilibrium transmission capacities might differ.

Finally, the effects of different price caps, demand response, production intermittency and predictability should be analysed. This model could also be used to analyze the impact of subsidized, very low marginal costs renewables on cross-border investment incentives. Felder (2011), OECD (2013) and Newbery et al. (2018) show that the long-run impacts of renewables on cross-border investments might be significant. We believe much of our previous results would carry over: low marginal cost renewables may provide cheap energy to neighbors in the short-run, but may also yield consequences on investments in dispatchable generation in either country. Cross-border contractual agreements or harmonized RES policy may therefore be needed.

Bibliography

ACER (2011). Framework Guideline on Capacity Allocation and Congestion Management for Electricity. Technical report.

ACER (2013). Capacity remuneration mechanisms and the internal market for electricity. Technical report.

Adib, P., Schubert, E., and Oren, S. (2008). *Chapter 9: Resource Adequacy: Alternate Perspectives and Divergent Paths.*

Antweiler, W. (2016). Cross-border trade in electricity. *Journal of International Economics*, 101:42–51.

Batlle, C. and Rodilla, P. (2010). A critical assessment of the different approaches aimed to secure electricity generation supply. *Energy Policy*, 38(11):7169–7179.

Bhagwat, P. C., Iychettira, K., and De Vries, L. J. (2014). Cross-border effects of capacity mechanisms. In *International Conference on the European Energy Market, EEM.*

Bhagwat, P. C., Richstein, J. C., Chappin, E. J., Iychettira, K. K., and De Vries, L. J. (2017). Cross-border effects of capacity mechanisms in interconnected power systems. *Utilities Policy.*

BMWi (2015). Joint Declaration on Regional Cooperation on Security of Supply in the Framework of the Internal Energy Market. Technical report.

Borenstein, S., Bushnell, J., and Stoft, S. (2000). The Competitive Effects of Transmission Capacity in a Deregulated Electricity Industry. *The RAND Journal of Economics*, 31(2):294.

CEER (2013). CEER views on the Commission's Public Interventions Package: Delivering the internal electricity market and making the most of public intervention. Technical report.

Cepeda, M. (2018). Assessing cross-border integration of capacity mechanisms in coupled electricity markets.

Cepeda, M. and Finon, D. (2011). Generation capacity adequacy in interdependent electricity markets. *Energy Policy*, 39:3128–3143.

Cramton, P. and Stoft, S. (2006). The convergence of market designs for adequate generating capacity with special attention to the CAISO's resource adequacy problem. *Berkeley, California, White Paper for the Electricity Oversight Board*.

Creti, A. and Fabra, N. (2007). Supply security and short-run capacity markets for electricity. *Energy Economics*, 29:259–276.

Creti, A. and Fumagalli, E. (2010). Integration of electricitymarkets in Europe: relevant issues for Italy. *Energy Policy*, (38):6966–6976.

De Vries, L. J. (2007). Generation adequacy: Helping the market do its job. *Utilities Policy*, 15(1):20–35.

Elberg, C. (2014). Cross-border effects of capacity mechanisms in Electricity Markets.

Eurelectric (2015). A reference model for european capacity markets. Technical report.

Eurelectric (2016). DG COMP interim report of the sector inquiry on capacity mechanisms. Technical report.

European Commission (2010). Communication from the Commission: Energy 2020. A Strategy for Competitive, Sustainable and Secure Energy. Technical report.

European Commission (2015). Energy union package: communication from the commission to the european parliament, the council, the european economic and social committee, the committee of the regions and the european investment bank. A framework strategy for a resilient energy union.

European Commission (2016a). Clean Energy For All Europeans. *Communication from The Commission to The European Parliament, The Council, The European Economic and Social Committee and The Committee of The Regions*, COM(2016)(860 final).

European Commission (2016b). Interim Report of the Sector Inquiry on Capacity Mechanisms. Technical report.

European Commission (2016c). Interim Report of the Sector Inquiry on Capacity Mechanisms. Technical report.

Fabra, N. (2018). A Primer on Capacity Mechanisms. *Cambridge Working Paper in Economics*.

Felder, F. A. (2011). Examining Electricity Price Suppression Due to Renewable Resources and Other Grid Investments. *Electricity Journal*, 24:34–46.

Frontier Econonomics (2015). Cross border participation in CRMs. Technical report.

FTI-Compass Lexecon energy (2016). Options for the future of power system regional coordination. Technical report, for ENSTO-E.

Gore, O. and Meyer, R. (2015). Cross-Border Effects of Capacity Mechanisms: Do Uncoordinated Market Design Policies Countervail the Goals of European Market Integration? *Energy Economics*, 51:9–20.

HayaEnergy (2017). Le mécanisme de capacité français en bonne voie pour prendre de l'avance sur les règles européennes.

Höschle, H., De Jonghe, C., Six, D., and Belmans, R. (2016). Influence of non-harmonized capacity mechanisms in an interconnected power system on generation adequacy. In *19th Power Systems Computation Conference, PSCC 2016*.

IEA (2014). Seamless power markets. Technical report.

Jamasb, T. and Pollitt, M. (2005). Electricity market reform in the European Union: review of progress toward liberalization & integration. *Energy Journal*.

Léautier, T. O. (2000). Regulation of an electric power transmission company. *Energy Journal*, 21(4):61–92.

Linklaters (2014). Reigniting Europe's energy markets. Technical report.

Mastropietro, P., Rodilla, P., and Batlle, C. (2014). National capacity mechanisms in the European Internal Energy Market: opening the doors to neighbours. *Energy Policy*, 82:38–47.

Mastropietro, P., Rodilla, P., and Batlle, C. (2015). The unfolding of regional electricity markets: measures to improve the firmness of cross-border trading.

McInerney, C. and Bunn, D. (2013). Valuation anomalies for interconnector transmission rights. *Energy Policy*, 55:565–578.

National Grid (2016). Electricity Capacity Report. Technical report, (submitted to DECC).

Newbery, D., Pollitt, M. G., Ritz, R. A., and Strielkowski, W. (2018). Market design for a high-renewables European electricity system.

OECD (2013). Cross-border trade in electricity and the development of renewablesbased electric power: lessons from europe. Technical report.

RAP (2013). Capacity Markets and European Market Coupling – Can they Co-Exist? Technical report.

RTE (2016). Méthodologie de calcul des capacités d'échanges transfrontaliers d'électricité appliquée par RTE aux frontières françaises. Technical report.

Stoft, S. (2003). Power System Economics: Designing Markets for Electricity.

Sweco (2014). Capacity Markets in Europe: Impacts on Trade and Investments. Technical report.

Tangerås, T. P. (2018). Equilibrium supply security in a multinational electricity market with renewable production. *Energy Economics*.

Thema (2013). Capacity mechanisms in individual markets within the IEM. Technical report.

Tirole, J. (1988). *The theory of industrial organization*.

Van den Bergh, K., Bruninx, K., and Delarue, E. (2018). Cross-border reserve markets: network constraints in cross-border reserve procurement. *Energy Policy*.

Viljainen, S., Makkonen, M., Gore, O., Kuleshov, D., and Vasileva, E. (2013). Cross-border electricity trade between the Nordic 'energy-only' market and the Russian capacitybased market. Technical report, Fingrid.

A Scattered national Capacity Remuneration Mechanisms

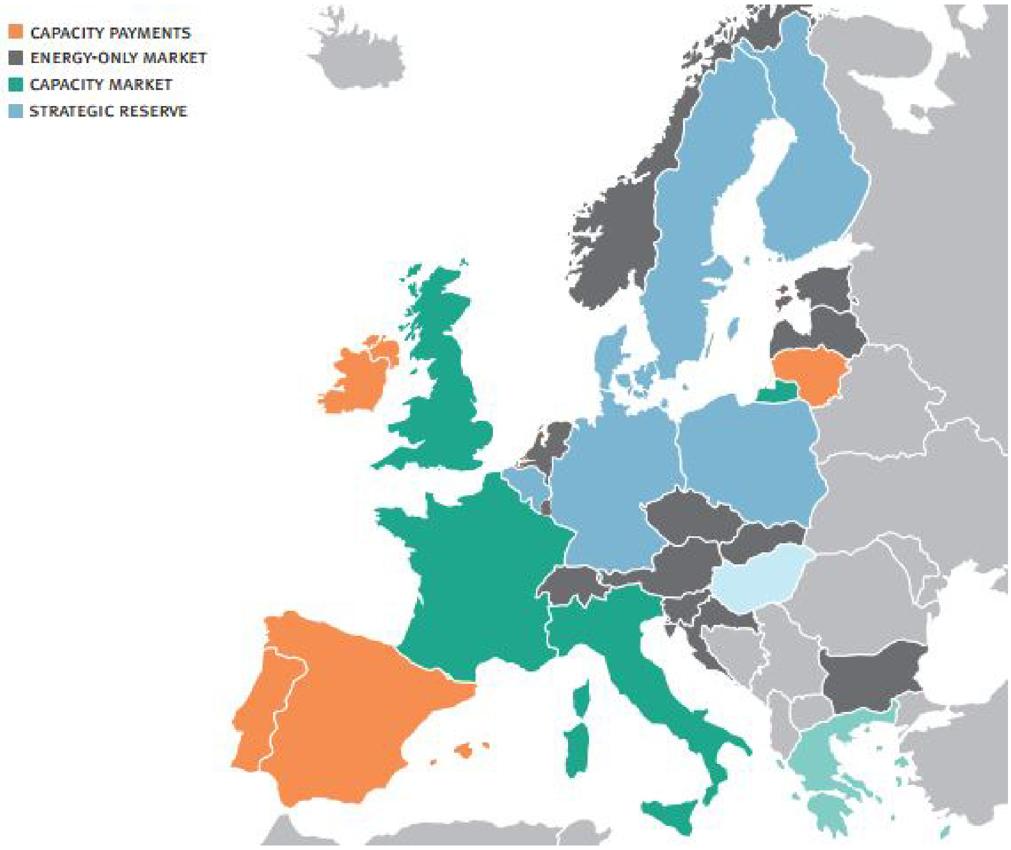


Figure 4.3: Source: Eurelectric, 2016

B Social cost of SoS

Comparing net surplus in an Energy-only market with net surplus in a market with a CRM, we can compute the social costs of Security of Supply. The net surplus decrease of an SoS level obtained with capacity $\bar{k}$ is[11]: $\Delta W^i(\bar{k}) = (\bar{P} - c)\left(\int_{k^*}^{\bar{k}} (\bar{k} - l) f(l) dl\right)$. Figure 4.4 shows that not only the total cost, but also the marginal total cost of support for capacity is increasing in the capacity target. The rationale is that when total capacity is just above the market equilibrium, the last added unit is still almost profitable: only a small amount of subsidy is required. Conversely when total capacity is large, the last unit is unlikely to be much used in the market (and therefore, unlikely to have any social value): the cost to consumers approaches r when $\bar{k} \to \infty$.

[11] note that this cost does depend on r, as k^* is a function of r

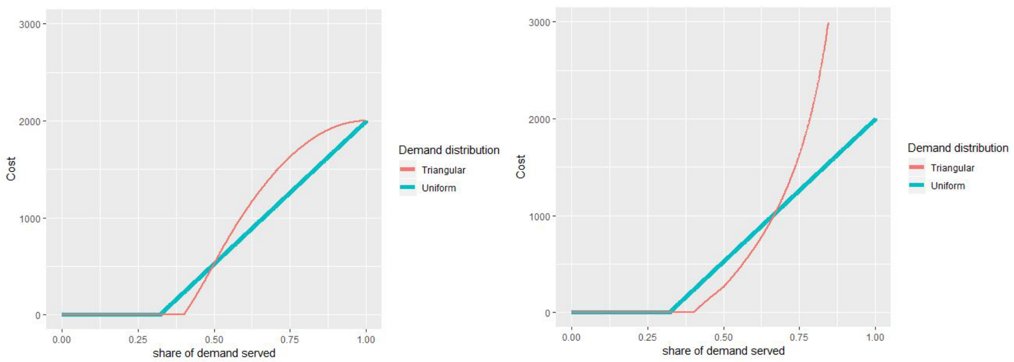
Proposition .3. *When markets are isolated, the social cost of a marginal capacity addition is close to zero for the first added units, and monotonically increases to r when total capacity approaches maximum demand.*

Proof. Using Equation (1.5), the marginal social cost of an additional unit of reserve capacity is:

$$-\frac{\partial W^i_{CM}}{\partial \bar{k}} = r - (\bar{P} - c)\left[1 - F(\bar{k})\right] = (\bar{P} - c)\left[F(\bar{k}) - F(k^*)\right] > 0$$

The marginal social cost of an additional unit of demand coverage:

$$-\frac{\frac{\partial W^i_{CM}}{\partial \bar{k}}}{\frac{\partial F(\bar{k})}{\partial \bar{k}}} = \frac{r}{f(\bar{k})} - (\bar{P} - c)\frac{1 - F(\bar{k})}{f(\bar{k})} = (\bar{P} - c)\frac{F(\bar{k}) - F(k^*)}{f(\bar{k})} > 0$$



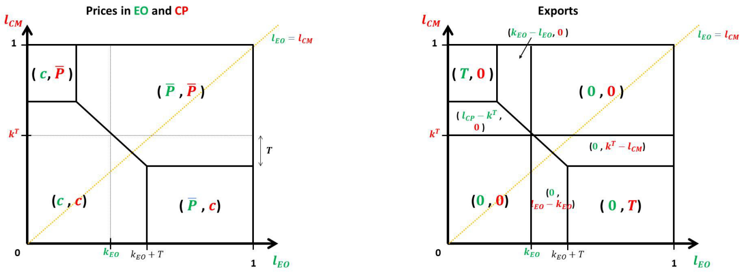
(a) (b)

Figure 4.4: Marginal social cost of extra capacity (left) and Marginal social cost of demand coverage(right), when demand follows a uniform distribution (thick line) or triangular demand distributions over $[0, 1]$ (thin line).
$r = 2000$, $\bar{P} = 3000$, $c = 50$

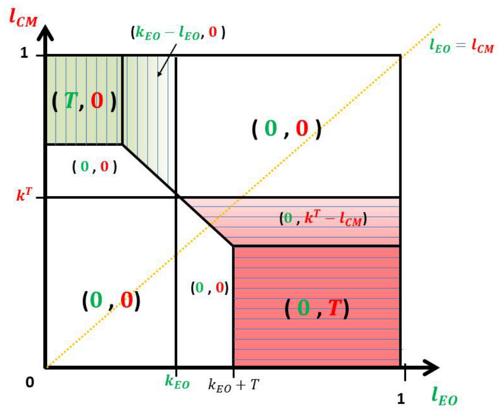
□

C Interconnected EO/CM markets – general case

We now relax the assumption that $l_{EO} = l_{CM}$. Thus, l is now bidimensional, and $l = (l_{CM}, l_{EO})$, distributed according to PDF $f(l)$. Name $F_s(.)$ the CDF of the *sum* of both demands: $F_s(K) = \mathbb{P}(l_{CM} + l_{EO} \leq K)$. Figure 4.5 shows the equilibrium prices, imports and profits made abroad when CM and EO are interconnected. It assumes the exporter owns the transmission rights.



(a)



(b)

Figure 4.5: Prices in market EO and CM (top left), Exports (top right) and profits made abroad (bottom) as a function of demand l_{EO} and l_{CM}. Horizontally (vertically) hatched areas indicate profits made by CM in EO (EO in CM). In this graph, transmission is never binding if loads are perfectly correlated ($l_{EO} = l_{CM}$).

C.1 Transmission is never binding

Free-entry

Assume that transmission is never binding ($T \to +\infty$). By free-entry in the energy-only market, we have that:

$$r = (\bar{P} - c)\,(1 - F_s(k_{CM} + k_{EO})) \tag{A1.20}$$

, as long as $k_{EO} > 0$. Assuming that the capacity market in the neighboring market is m, free-entry in the CRM market yields

$$r = m + (\bar{P} - c)(1 - F_s(k_{CM} + k_{EO})) \tag{A1.21}$$

We thus find again that as long as there is still some economically viable capacity in the energy-only market, we must have that $m = 0$: CM's CRM comes at zero upfront cost.

Denote K^{eq} the total equilibrium level of capacity: $K^{eq} = k_{EO} + k_{CM} = F_s^{-1}\left(1 - \frac{r}{\bar{P}-c}\right)$. k_{CM} will be pinned down by CM's SoS target. In turn k_{EO}, will be set by the free entry condition in EO (A1.20).

Curtailment levels

Assume that absent intervention, capacity in each market (αK^{eq} in CM, $(1-\alpha)K^{eq}$ in EO) is such that the EENS are same in both markets. Assume further that:

$$\bar{\mathcal{L}}_{CM} \leq \mathcal{L}_{CM}(\alpha K^{eq}, (1-\alpha)K^{eq}) = \mathcal{L}_{EO}(\alpha K^{eq}, (1-\alpha)K^{eq}) \leq \bar{\mathcal{L}}_{EO}$$

Where the first inequality means CM's maximum expected curtailment is less than the equilibrium one (hence the need to implement a CRM). The equality states formally that without CRMs, the EENS is the same in both countries. The last inequality means market EO does not need to implement a CRM if CM doesn't. Optimality requires that CM just meets (and does not exceed) its SoS target $\bar{\mathcal{L}}_{CM}$. There can be some curtailment in CM only if (1) both markets are tight or (2) EO has excess capacity but it doesn't suffice to meet both EO and CM demands. Thus, we can write:

$$\begin{aligned}
\bar{\mathcal{L}}_{CM} =& \mathcal{L}_{CM}(\bar{k}, K^{eq} - \bar{k}) \\
=& \overbrace{\iint_{\substack{l_{CM} \geq k_{CM} \\ l_{EO} > k_{EO}}} (l_{CM} - k_{CM}) f(l) dl}^{\text{both markets are tight}} \\
&+ \overbrace{\iint_{\substack{l_{EO} \leq k_{EO} \\ l_{CM} + l_{EO} > k_{CM} + k_{EO}}} (l_{CM} - (k_{CM} + k_{EO} - l_{EO})) f(l) dl}^{\text{EO loose, but regional market tight}} \\
=& \iint_{\substack{l_{CM} \geq \bar{k} \\ l_{EO} > K^{eq} - \bar{k}}} (l_{CM} - \bar{k}) f(l) dl + \iint_{\substack{l_{EO} \leq K^{eq} - \bar{k} \\ l_{CM} + l_{EO} > K^{eq}}} (l_{CM} + l_{EO} - K^{eq}) f(l) dl
\end{aligned}$$

We have that $\mathcal{L}_{CM}(\bar{k}, K^{eq} - \bar{k})$ monotonically decreases in $\bar{k}$. $\mathcal{L}_{CM}(\bar{l}_{CM}, K^{eq} - \bar{l}_{CM}) = 0 < \bar{\mathcal{L}}_{CM}$, and $\mathcal{L}_{CM}(\alpha K^{eq}, (1-\alpha)K^{eq}) = \mathcal{L}_{EO}(\alpha K^{eq}, (1-\alpha)K^{eq}) > \bar{\mathcal{L}}_{CM}$. Thus, there exists a unique $\bar{k}$ such that CM meets its maximum expected curtailment target at least cost. k_{EO} is then pinned down by free entry in the energy-only market: $k_{EO} = K^{eq} - \bar{k}$, such that total capacity remains optimal, whatever is the target CM. The impact on EO's expected curtailment, when $\bar{k} \leq K^{eq}$ is:

$$\mathcal{L}_{EO}(\bar{k}, K^{eq} - \bar{k}) = \iint_{\substack{l_{CM} \geq \bar{k} \\ l_{EO} > k_{EO}}} (l_{EO} - (K^{eq} - \bar{k}))f(l)dl + \iint_{\substack{l_{CM} \leq \bar{k} \\ l_{CM} + l_{EO} > K^{eq}}} (l_{CM} + l_{EO} - K^{eq}))f(l)dl$$

The first term is the expected curtailment when both markets are tight, and the second one means CM has excess capacity, but its exports are not sufficient for EO to meet its local demand. One observes that $\mathcal{L}_{EO}(\bar{k}, K^{eq} - \bar{k})$ monotonically increases in $\bar{k}$. If $\bar{k} \leq \alpha K^{eq}$ (i.e. CM doesn't need to build a CRM), $\mathcal{L}_{EO}(\bar{k}, K^{eq} - \bar{k}) < \bar{\mathcal{L}}_{EO}$, and EO doesn't need to implement a CRM either. If $\bar{k} > \alpha K^{eq}$ (i.e. if CM implements a CRM) we have $\mathcal{L}_{EO}(\bar{k}, K^{eq} - \bar{k}) > \mathcal{L}_{EO}(\alpha K^{eq}, (1-\alpha)K^{eq})$. If $\bar{k} = K^{eq}$, we have that $k_{EO} = 0$. Then the expected curtailment in EO is high, as EO relies exclusively on CM's exports. When the target in CM is so large that it exceeds the equilibrium total capacity, ($\bar{k} \geq K^{eq}$) we have:

$$\mathcal{L}_{EO}(\bar{k}, 0) = \iint_{l_{CM} \geq \bar{k}} l_{EO} f(l)dl + \iint_{\substack{l_{CM} \leq \bar{k} \\ l_{CM} + l_{EO} > k^T}} (l_{CM} + l_{EO} - k^T))f(l)dl$$

This expected curtailment is *decreasing* in $\bar{k}$ and can be lower or greater than $\bar{\mathcal{L}}_{EO}$. Note that $\mathcal{L}_{EO}(\bar{k}) \underset{\bar{k}\to\infty}{\to} 0$, meaning if CM's aversion to curtailment is extremely high, EO might actually benefit from it, both in terms of SoS and consumer costs. Figure 4.6 gives an illustration of the expected curtailment in EO when CM implements a capacity market. When the expected curtailment is higher than the target (red area), EO will have to implement a CRM as well.

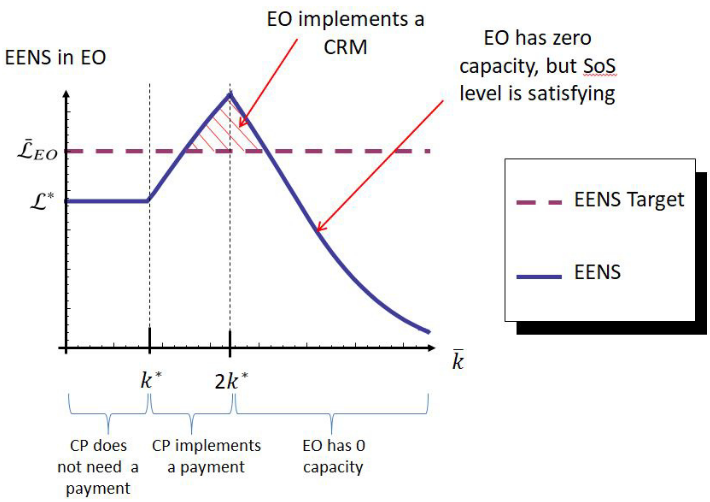


Figure 4.6: Expected curtailment in EO (solid line) for i.i.d demand following a uniform distribution over $[0, 1]$. Expected curtailment increases with $\bar{k}$, and then decreases when capacity in EO reaches 0. For some region, EO will be forced to implement a CRM in order to meet its SoS standard (dotted line, level is illustrative). $r = 500$, $c = 50$,$T = +\infty$, $\bar{P} = 700$

Welfare analysis

Let us focus on the more realistic case when $\bar{k} \leq K^{eq}$. As long as $\bar{k} < K^{eq}$, total capacity in the system is the optimal level K^{eq}. Therefore, the overall system remains optimal and only the allocation of net surplus between EO an CM will be affected.

Net surplus in market CM can be calculated as:

$$W_{CM} = \overbrace{(\bar{P} - c) \iint_{l_{CM} + l_{EO} \leq K^{eq}} l_{CM} f(l) dl}^{no\ overall\ scarcity} - \overbrace{\bar{k} * m}^{\text{capacity market}}$$

$$+ (\bar{P} - \bar{P}) \Bigg(\overbrace{\iint_{\substack{l_{CM} \leq \bar{k} \\ l_{CM} + l_{EO} \geq K^{eq}}} l_{EO} f(l) dl}^{\text{EO tight}} + \overbrace{\iint_{\substack{l_{CM} \geq \bar{k} \\ l_{EO} \geq K^{eq} - \bar{k}}} \bar{k} f(l) dl}^{\text{both markets tight}}$$

$$+ \overbrace{\iint_{\substack{l_{EO} \leq K^{eq} - \bar{k} \\ l_{CM} + l_{EO} \geq K^{eq}}} (K^{eq} - l_{EO}) f(l) dl}^{\text{CM tight}} \Bigg)$$

given that $m = 0$:

$$=(\bar{P} - c) \iint_{l_{CM} + l_{EO} \leq K^{eq}} l_{CM} f(l) dl \tag{A1.22}$$

Again, notice that net surplus in CM does not depend on $\bar{k}$, while demand coverage has increased: similarly to the case with correlated demands the support scheme comes without a loss in net surplus. Given that total net surplus is insensitive to $\bar{k}$, we can verify that net surplus in market EO is also insensitive to $\bar{k}$:

$$W_{EO} =(\bar{P} - c) \iint_{l_{CM} + l_{EO} \leq K^{eq}} l_{EO} f(l) dl$$

The CRM in CM does not modify net surplus in EO, but decreases its SoS level. If $\mathcal{L}_{EO}(\bar{k}, k_{EO}) > \bar{\mathcal{L}}_{EO}$, EO will implement a CRM as well. It can be either a strategic reserve or some form of capacity market. Those cases are discussed in Section 5. The main conclusion of this subsection can be summarized as follows:

Proposition .4. *If a market unilaterally implements a capacity market and physical transmission capacity is never biding but TSOs may reduce export capacity at times of scarcity, a neighboring energy-only market endures a capacity decrease, equivalent to the incremental capacity in the capacity market market. Net surplus is unchanged in the EO market, but SoS decreases by the same amount as it increases in the CM market.*

Proof. Follows from previous developments □

C.2 Transmission is binding

So far, we have assumed that the transmission line was never congested. However, a transmission line with an optimal size should be congested sometimes, so that the fixed costs of investment in transmission are recovered through the congestion rent (see e.g. Léautier (2000), Borenstein et al. (2000). Assume now that transmission can be congested, i.e. $\mathbb{P}(l_{CM} - k_{CM} > T \cap k_{EO} - l_{EO} > T) + \mathbb{P}(l_{EO} - k_{EO} > T \cap k_{CM} - l_{CM} > T) > 0$.

The free entry conditions are:

$$r = (\bar{P} - c) \left(\overbrace{\iint_{\substack{k_{EO} + T < l_{EO} \\ l_{CM} \leq k_{CM} - T}} f(l)dl}^{\text{EO tight, transmission congested}} + \overbrace{\iint_{\substack{l_{EO} \geq k_{EO} - T, l_{CM} \geq k_{CM} - T \\ l_{CM} + l_{EO} \geq K^{eq}}} f(l)dl}^{\text{EO and CM tight}} \right) \tag{A1.23}$$

$$r = (\bar{P} - c) \left(\iint_{\substack{k_{CM} + T < l_{CM} \\ l_{EO} \leq k_{EO} - T}} f(l)dl + \iint_{\substack{l_{EO} \geq k_{EO} - T, l_{CM} \geq k_{CM} - T \\ l_{CM} + l_{EO} \geq K^{eq}}} f(l)dl \right) + m \tag{A1.24}$$

$$\Rightarrow m = (\bar{P} - c) \left(\iint_{\substack{k_{EO} + T < l_{EO} \\ l_{CM} \leq k_{CM} - T}} f(l)dl - \iint_{\substack{k_{CM} + T < l_{CM} \\ l_{EO} \leq k_{EO} - T}} f(l)dl \right) > 0 \tag{A1.25}$$

As a consequence of limited transmission capacity, capacity in CM is no longer a perfect substitute to EO's capacity, and CM will enjoy less high-priced exports. Therefore CM's TSO has to provide a strictly positive amount of support to capacity. Equilibrium capacities will be set by the free-entry condition in EO (A1.23) and CM's SoS target:

$$\begin{aligned}
\bar{\mathcal{L}}_{CM} =& \mathcal{L}_{CM}(\bar{k}, k_{EO}(\bar{k})) \\
=& \overbrace{\iint_{\substack{l_{CM} \geq \bar{k} \\ l_{EO} > k_{EO}}} (l_{CM} - \bar{k}) f(l)dl}^{\text{both markets are tight}} \\
& + \overbrace{\iint_{\substack{k_{EO} - T \leq l_{EO} \leq k_{EO} \\ l_{CM} + l_{EO} > \bar{k} + k_{EO}}} (l_{CM} - (\bar{k} + k_{EO} - l_{EO})) f(l)dl}^{\text{total capacity unsufficient}} \\
& + \underbrace{\iint_{\substack{l_{EO} \leq k - T \\ l_{CM} > \bar{k} + T}} (l_{CM} - (\bar{k} + T)) f(l)dl}_{\text{transmission capacity unsufficient}}
\end{aligned} \tag{A1.26}$$

Unfortunately the system of equations (A1.23,A1.25,A1.26) has no closed-form solution. Figure 4.7 proposes an illustration of the effect of a neighbouring CM on local EENS. Figure 4.7 is equivalent to Figure 4.6, but with a transmission line that can be congested. For a given level of SoS in CM, SoS in EO is higher than in the "no congestion" case, as limited capacity protects EO's plants from CM's competition: A smaller transmission line means it is less likely that the energy-only neighbor will have to implement a CRM. In fact, for very small transmission capacity, and an energy-only market that's far enough from its expected curtailment limit, interconnection will have no impact on net surplus in the energy-only market. On top of that, if market EO gets at least a small part of the congestion rent, interconnection provides additional revenues to the energy-only market, translating in an increase in net surplus compared to an isolated or EO/EO case.

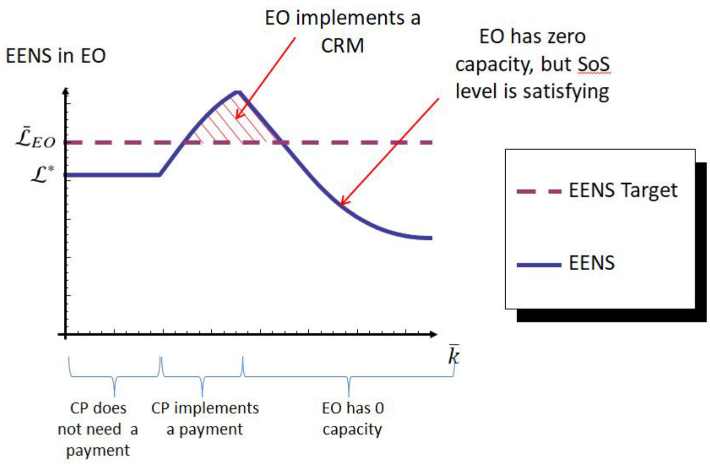


Figure 4.7: Expected curtailment in EO (solid line) for i.i.d demand following a uniform distribution over $[0, 1]$. Expected curtailment increases with $\bar{k}$, and then decreases when capacity in EO reaches 0. For some SoS levels in CM, EO will be forced to implement a CRM in order to meet its SoS standard (dotted line, level is illustrative). $T = 0.2$, $r = 500$, $c = 50$, $\bar{P} = 700$

D Graphic representation of supply and demand balances

Graphs for perfectly symmetric demand, distributed on $[0, 1]$, infinite transmission capacity.

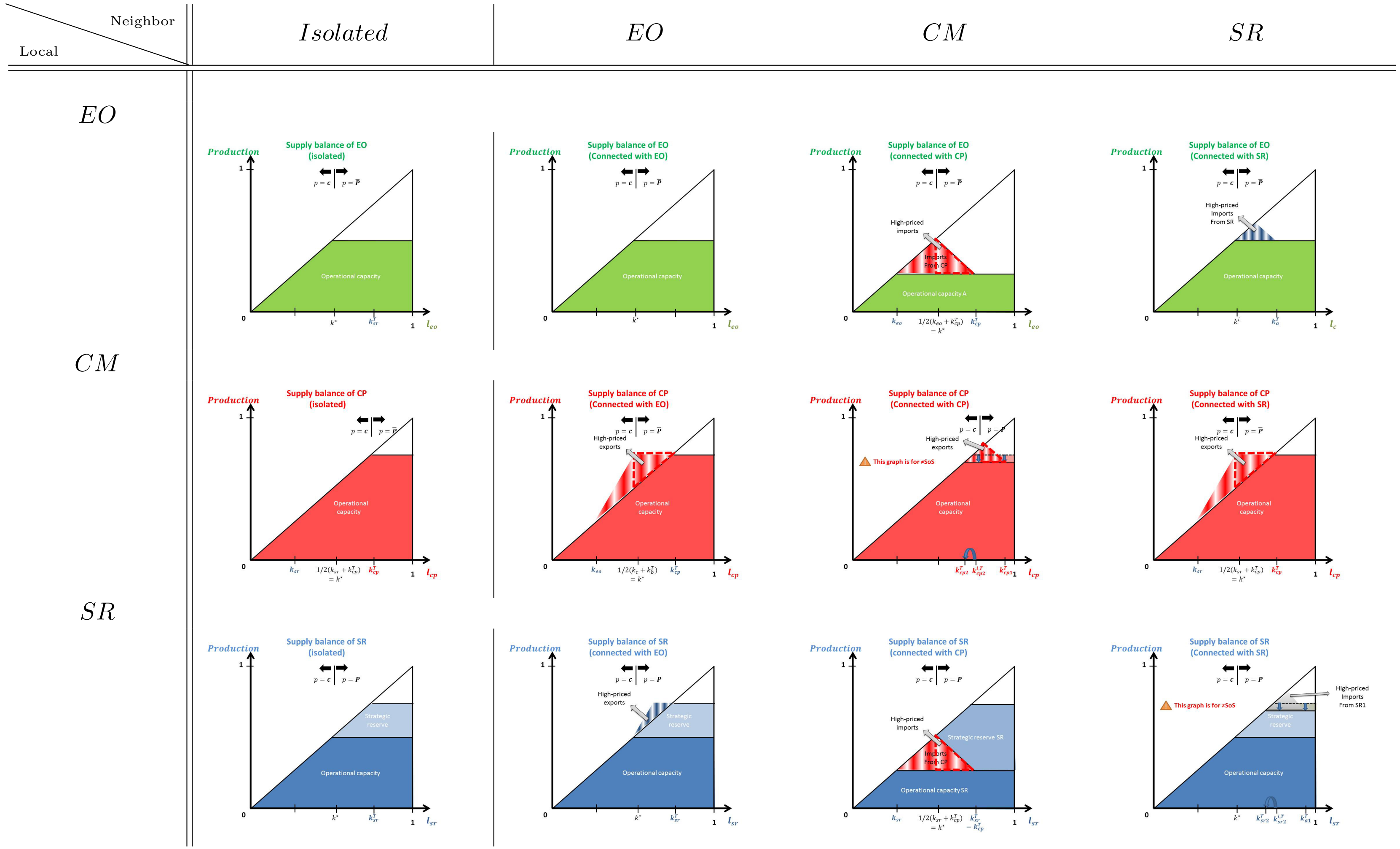


Figure 4.8: Supply as a function of demand. Demand in both market is perfectly correlated.

Chapter 2

The integration of demand response in capacity remuneration mechanisms

About this chapter

I am very grateful to Andreas Ehrenmann and ENGIE's Center of Expertise in Economic Modeling and Studies for insightful discussions that motivated this project. I'm also indebted to Thomas-Olivier Léautier, Estelle Cantillon, Claude Crampes, Nicolas Astier and participants of TIERCE seminars in Toulouse School of Economics for very valuable questions and comments. I also thank participants of the YEEES 2016 conference, the CIES summer school 2017, the Toulouse conference on energy economics 2017 and the IAEE 2018 for useful comments and feedbacks. This research was supported by ENGIE and the H2020-MSCA-RISE project GEMCLIME-2020 GA No. 681228.

A related paper co-written with Nicolas Astier (Astier and Lambin, 2019) uses a similar framework. It focuses on the political and informational challenges that impede the optimal design for incentives schemes for capacity and demand-response deployment. This paper has been published in the Energy Journal, and is not included in the present dissertation.

Abstract

Various market failures inherent to electricity markets have prompted regulators to ensure the power system can meet demand peaks. On the supply side, one can support capacity through a Capacity Remuneration Mechanism. On the demand side, Demand Response (DR) technologies can be rolled out. We find that if DR is not price-responsive but instead waits for activation to be requested by the transmission system operator, its contribution to security of supply is less than traditional generation. We conclude that while all traditional generation should receive the same payment, the payment for capacity to DR technologies should be weakly decreasing in the operator's position in the load-shedding order. For stylized DR technologies, a menu of screening contracts implementing the first-best investment and activation is provided. We observe that all schemes currently implemented provide inadequate incentives to non-price responsive DR and propose to de-rate payments to DR units as a function of their expected activation periods.

Keywords- Demand response, Capacity remuneration mechanisms, Power market design, Priority service

1 Introduction

The liberalization of the energy sector and the fast development of renewable energy sources have deeply modified the economic environment investors are navigating. Many European regulators are now implementing some form of Capacity Remuneration Mechanism (CRM), in order to increase demand coverage beyond what the energy market alone provides. What is an adequate remuneration structure and level for capacity remains actively debated in many European countries. An intuitive alternative to building more capacity is to encourage demand-response.[1] Indeed, in times of scarcity a transmission system operator (TSO) may identify consumers who need electricity the least, and have their load reduced in exchange for a financial compensation. This strategy may prove very effective: Gray Davis, governor of California during the California electricity crisis noted that he "could have solved the problem in 20 minutes" had he been able to pass through the rising prices to consumers, a statement confirmed by numerous

[1]Throughout this paper we will stick to FERC's definition of DR as "changes in electric use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized", see Federal Energy Regulatory Commission (2015)

academic studies (Borenstein (2005), Faruqui et al. (2009)). ENTSO-E (2015) stresses that DR "often has a high capacity value relative to its energy value in many countries. Participation in reserve capacity markets therefore opens significant opportunities for the development of DR and provides an additional revenue stream for DR capacities that can match technical requirements". In turn, the EU state-aid guidelines state that Demand-side management development should be an explicit target of any CRM.[2] Thus, the question of DR contribution to adequacy and its integration in CRMs needs to be tackled. The subject has however been surprisingly under-studied in the academic literature. Much of the focus of previous research has been on assessing the technical potential of DR, but little has been done on market design. Regulators and TSOs are thus left with little theoretical guidance, leading to a patchwork of assorted designs. As an illustration, the Smart Energy Demand Coalition (2015b) maps European Member States progresses in providing adequate conditions for DR development, showing strong disparity.

The originality of the present work is to link the concepts of DR and CRMs, and show how the former can be integrated in the latter. In our model, capacity remuneration is needed because of the presence of a price cap, which in turns creates a "missing money" problem and makes prices and DR activation inefficient. The status-quo regulation is to say that DR is technically not capacity, and therefore should not receive any remuneration from the CRM –set aside implicit remuneration through energy market prices. Another extreme is to consider that DR is exactly like capacity, and should therefore receive a full payment. Most technology-specific CRMs (Spanish capacity payments to new combined-cycle gas turbines, German strategic reserve composed of ageing coal plants...) or generation-only schemes fall by default in the first category. Market-wide CRMs that allow explicit DR participation such as the British, French or PJM CRMs are in the second category.[3] However, our paper argues that the optimal solution lies between these two extremes, with an optimal payment that should depend on the ranking of the DR service in the activation order. If a DR operator –who we define as an electricity consumer having installed a technology enabling him to manage his load according to

[2]The Energy Efficiency Directive Article 15.8 states that "Member States shall promote access to and participation of demand response in reserve markets". The Guidelines on State aid for environmental protection and energy 2014-2020 art. 224 require the member states to provide an "assessment of the impact of demand-side participation, including a description of measures to encourage demand side management" , http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX% 3A52014XC0628(01)

[3]Remuneration per unit of capacity is derated to take account of particularities of DR such as reduced availability compared to traditional generation or longer activation notice –see e.g. National Grid (2017) for details. However, no de-rating is applied to take account of the activation probability of each DR installation.

market conditions or a request from the TSO – commits to activating at least when prices are at the price cap, then this service is indeed equivalent to the one offered by dispatchable generation and the DR operator should receive a full payment for capacity. If DR activation is not prompted by market prices, but awaits a TSO order, then the payment should be smaller, as it is not activated as often as market-based DR is. The less it is activated, the less valuable the service, and the lower the payment should be if the TSO wants to make sure there is optimal investment in DR.

The intuition is rather straightforward. Let's imagine a system where all consumers are non-price responsive, apart from a substantial amount of industrial players whose opportunity costs lie between the price cap and the system value-of-lost-load. Assume there are enough industrial players so that random curtailment of non-price responsive consumers is never needed. The DR operator with highest opportunity cost is never requested to shed load, meaning he provides no welfare gain and should therefore receive no payment –even if the operator is technically available for load reduction. This does not mean, however, that none of the DR operators should receive a payment for capacity. Price-responsive DR, just like traditional generation, does endure a missing money problem: when DR is activated, prices may be stuck at the price cap, while the marginal value of electricity is that of the fringe DR operator – which may be (much) higher than the price cap. A strictly positive compensation payment is therefore required to restore optimal investment incentives to price-responsive DR. The present paper provides a formal analysis of this intuition.

The remainder of the paper is organized as follows. Section 2 reviews the literature relevant to our analysis. Section 3 sets up a simple analytical model. Section 4 exhibits contracts that elicit optimal DR participation. Section 5 relates our findings to the current state of regulation and Section 8 concludes.

2 Literature review

This paper relates mainly to three streams of literature.

First, it contributes to the discussion on DR market design. Comprehensive overviews of the variety of potential market designs for DR can be found in Behrangrad (2015) or Warren (2015). DR may yield many benefits beyond CRMs, including improving grid management and investments, helping integrate renewables, improving allocative efficiency of the power system, reducing power prices.[4] The potential for development is

[4]Strbac (2008), Borenstein et al. (2002), Borenstein (2005) ; Borenstein (2002) ; Faruqui et al. (2007) ; Brophy Haney et al. (2009); Chao (2010); Hogan (2009), give thorough overviews of these benefits

substantial, with estimates as high as 52 GW in Europe.[5] Optimal rewards for such services have been discussed (among others) by Bushnell et al. (2009), Astier and Léautier (2016), where authors stress that the incentives should be price-based, especially if the baseline demand is unverifiable. Generally speaking, the benefits of price-responsive demand when prices are efficient have been described extensively, both in terms of short term benefits (allocative efficiency), and long term benefits through improved investment signals (Borenstein (2005), Borenstein and Holland (2003)). In this paper, we focus on the value of DR as a provider of capacity. DR's ability to contribute to adequacy has been demonstrated with simulations (Albadi and El-Saadany (2008), Aalami et al. (2010)), experiments (Faruqui and George (2005), Faruqui and Sergici (2010)) and again the technical and economic potential is estimated to be substantial (Borenstein and Holland (2003), Faruqui et al. (2007)). As an example Borenstein and Holland (2003) estimates that peak capacity in the U.S. could be decreased by 30 to 60 % if respectively one third or all consumers became price-responsive. For this potential to materialize, adequate market design needs to be implemented. The novelty of this work is to introduce inefficient pricing (by means of a price cap) in an analytical framework. We observe that the price cap leads to inefficient activation and deployment of DR technologies, and propose a new market design that corrects this shortcoming. Even though we expose our model in the case of DR operators who observe prices in real-time, the model applies both to price-based and incentive-based demand-response:[6] only the states of the world when DR is activated matter, whether this activation is prompted by prices or upon request from a grid operator.

Second, this paper complements the literature on CRMs. There is a wide variety of mechanisms, ranging from direct payments for capacity to reliability option or strategic reserves (See e.g. the works Adib et al., 2008, Batlle and Rodilla, 2010, Cramton and Stoft, 2006, De Vries, 2007 for critical reviews of these mechanisms). These mechanisms may be technology-neutral or not, centralized or decentralized, volume- or price-based.[7] However they all essentially consist in giving additional payments to some generators in order to make sure they will be available capacity at times of high demand.[8] This is the

[5] http://energy.sia-partners.com/20150205/demand-response-a-study-of-its-potential-in-europe

[6] Price-based DR refers to changes in usage by customers in response to changes in the prices they pay (e.g. real time pricing. Incentive-based DR refers to incentives separated from the retail electricity rate and can be offered by the grid operator or utilities. See US Department of Energy (2006) or Steen et al. (2012) for useful descriptions of these designs.

[7] See European Commission (2016), page 10 for a summary of these designs

[8] As such, there exists some scepticism over whether there is a real need for CRMs, and whether they constitute a state aid – see Léautier (2016), or the European Commission sector inquiry on electricity capacity mechanisms

only feature we need in our model, meaning the insights apply to all CRMs. CRMs have often been supported based on the "missing money" problem created by price caps (see e.g. Joskow, 2013, Cramton et al., 2013).[9] To take advantage of its formal simplicity, we will keep this motivation, leaving implementation details aside as they are not needed for our purpose. Most current CRM designs apply de-rating factors to take account of imperfections such as notification requirements or availability probability (see e.g. National Grid, 2016). The novelty of this paper is to propose to de-rate DR payments according to a new dimension, namely the DR operators' rank in the load-shedding plan.

Finally, our conclusions and the model we use are reminiscent of the work on priority services (see e.g. Marchand, 1974, Chao et al., 1986, Chao and Wilson, 1987): Assuming prices are capped below the value of lost load, one cannot rely solely on the benefits of spot pricing (as exposed in Caramanis et al. (1982), Schweppe (1988)) since prices sometimes do not convey all necessary information. Thus, some form of activation order needs to be implemented. This idea of a complementarity of priority service and spot markets was explored in Chao (2012), albeit in a move to correct other market imperfections (namely, the lack of hedging instruments in presence of risk aversion) than the one studied in this paper (price caps). In our case when the Principal is not biased against DR operators,[10] the priority pricing we propose replicates the efficient performance of a spot market, as in Wilson (1989).[11] The seminal work of Joskow and Tirole (2007) also studies optimal rationing and the effect of price caps and payments for capacity. A key novelty of the present model is that we endogenize investment decisions in DR technologies. Importantly, we allow payments for capacity to accrue not only to traditional generation but also to DR operators with high opportunity cost of consumption.

3 A simple framework

To keep the market design simple and convey the intuitions in a clear manner, we restrict ourselves to a very simple setting where only the value of consumption of DR operators matters. A TSO, the market designer, strives to maximize social welfare in its

[9] CRMs can also be defended on other grounds. For example, and importantly, there may be a need to compensate for a "missing market" for risk (see Newbery, 2016), leading to underinvestment in capacity.

[10] A good rationale for that is that DR operators are also consumers, and thus a Principal may want to give an equal weight on DR and non-DR consumer surpluses

[11] When spot markets are capped, all conditions outlined in Wilson (1989) for priority services to be useful are met: service sometimes needs to be rationed, consumers have diverse preferences (i.e. there are efficiency gains from differentiation), spot prices do not operate freely. In our model, customer preferences are perfectly consistent over time, meaning priority services can be efficient.

balancing zone. We assume it serves two categories of consumers.[12] The first category, which we name the "households" cannot be made price-responsive. For example it is composed of residential areas, where implementing a DR technology (for instance a smart meter, enabling to reduce heating when market prices are high) in each house would be prohibitively costly. Even though this assumption is made essentially to keep the model simple while conveying the intuition, we believe it is reasonably representative of small consumers: Léautier (2014) argues that rolling out smart meters in the residential sector may make little economic sense due to high installation costs and one should rather focus on bigger consumers,[13] a doubt already cast in Borenstein (2005) who suggests the additional gains from putting smaller customers on real-time pricing may not justify the costs. We assume that total household demand is stochastic over time. To keep the model parcimonious, the value of consumption per unit of energy is independent on household total demand and same for all consumers, set at a common knowledge V_h (h standing for "household"). The TSO also serves a second type of consumers, the "industry". It is composed of individual consumers for whom implementing a DR technology may be worth considering (say, those are industrial clients with typically large consumption levels). For simplicity again and contrary to stochastic household demand, each of these agents has constant unit demand (absent DR activation). Borrowing from Doucet and Roland (1993), this unit demand will be referred to as "desired demand" (i.e. served demand if supply were unconstrained). As desired demand is fixed, the literature on self-rationing based on capping consumer demand at times of scarcity (Panzar and Sibley (1978), Woo (1990), Doucet and Roland (1993)) cannot be applied. Instead, we focus on the reduction of consumption below the desired load. This reduction will be prompted either by prices or by ex-ante contracting that requires load reduction when household demand is high.

Each industrial agent i has a given value of consumption V_i per unit of energy. If he wants to decrease consumption in some states of the world (for example when prices are high), he needs first to install a DR technology, at a fixed cost. We believe this framework is general enough to cover most DR technologies. Both the value of consumption V_i and fixed costs are constant over time. They are both unknown to the TSO. However the

[12] In the literature on incentives and regulation, the TSO is the "principal", while industrial consumers are the "agents".

[13] Smart meter deployment costs have been estimated between \$ 95 and \$ 600 per consumer (see Faruqui et al., 2009). In California, the regulator has authorised a 4 billion dollars expense to replace 10.5 million meters. Faruqui et al. (2009) estimated deployment costs to 51 billion euros for a Europe-wide deployment. Rious et al. (2012) estimates 30 million meters deployed in France will cost between 4 and 8 billion euros. These estimates cast a doubt on the social desirability of smart meters for small consumers.

TSO knows that industrial consumers have, on average, a higher value of consumption than the consumers. Thus, in case there is scarcity and all available DR is already activated, the TSO chooses to curtail households instead of industrial players.[14] V_h is therefore the "value of lost load" of the system. However, the TSO also knows that *some* industrial consumers' characteristics can be such that costs of investment and activation can be lower than the system VoLL V_h, meaning it would be optimal to require these low-opportunity cost industrial consumers to install the DR technology and activate at times of scarcity instead of curtailing households. The market has a price cap $\bar{P} < V_h$, which is consistent with the the price cap being (much) lower than most value of lost load estimates.[15] Hence there is a so-called "missing-money" problem, which motivates the implementation of a CRM in the present paper – see e.g. Joskow (2013).

It is useful at this stage to note that the model does not take account of the (important) problems of asymmetry of information on volumes: industrial i's load without a DR technology is fixed and known both by the TSO and operator i. Also, we do not address the problem of consumers' contribution to CRMs: we consider that consumers have paid their contribution to the CRM – the level of which we do not discuss here– as required by the TSO, and we then wonder what should be the remuneration from the TSO, in order for consumers to agree to offer DR services. In other words, we assume consumers have paid ex-ante all costs associated with their baseline demand. This eliminates the arbitrage opportunities highlighted in Astier and Léautier (2016), whereby consumers can report a high "desired" consumption, and then re-sell an artificial load-shedding service. DR and traditional generation are assumed to be 100% reliable. We also assume that all agents are price-takers. These simplifications allow to focus on the opportunity cost of DR activation and its consequence on DR activation timing and optimal payment.

Figure 3.7 displays illustrative demand and supply curves when some DR is intalled. While some DR behaves like generation (price-responsive DR, with value of consumption below the price cap $\bar{P}$), other DR services with values of consumption higher than the price cap but lower than the system VoLL V_h need to be tied with a contract if the TSO

[14] These assumptions reflect the spirit of most shedding plans implemented by European TSOs. Typically, small, non-strategic industry are curtailed first, and then residential areas will be affected. Hospitals, defence facilities but also important industrial sites like harbours are excluded from the load-shedding plan. As an illustration, the interested reader may refer to the Belgian load-shedding plan Economie.fgov.be (2015).

[15] The market coupling algorithm Euphemia and European market places use a price cap of $\bar{P} = 3000$ €$/MWh$. The European Commission (see European Commission, 2016) stresses that "Where VOLL has been estimated by MSs it ranges from €$11,000/MWh$ to €$26,000/MWh$, so significantly higher than existing European price caps"

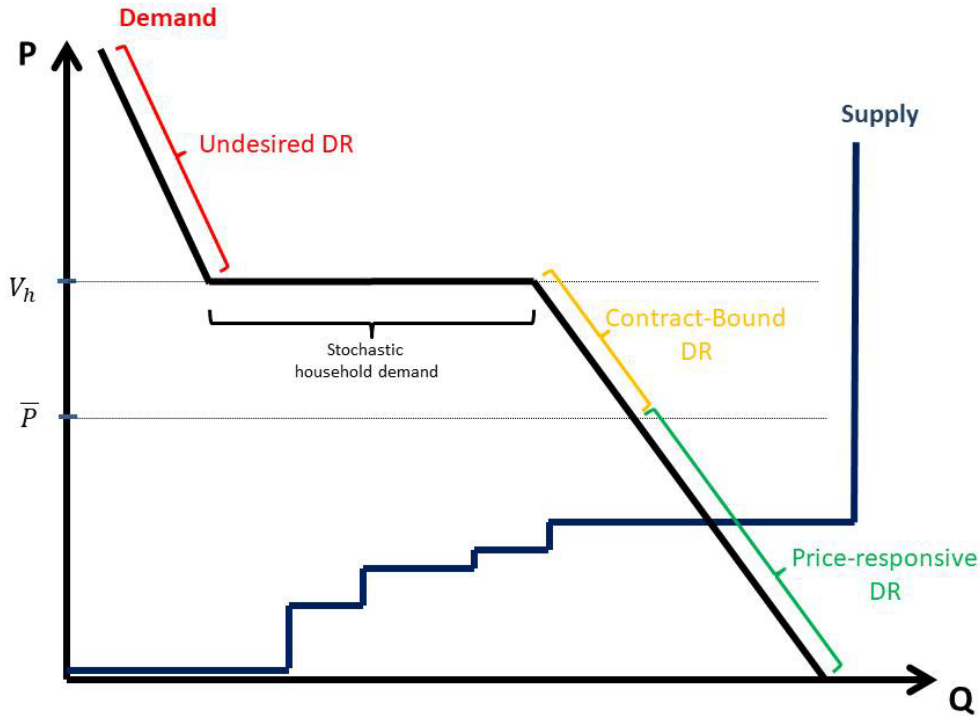


Figure 2.1: Illustrative electricity supply and demand curves

wants them to activate instead of curtailing households, as energy prices do not send the adequate activation signal. The amount of consumption that has such intermediate opportunity-cost is not negligible. Figures reported in table 106 of London Economics (2013) show that around 15% of industrial demand in the UK has an opportunity cost lying between the price cap and the average value of lost load. The novel insights of the present paper focus on this category of consumers.

We will exhibit a menu of complete contingent screening contracts that ensures that all available welfare-improving DR services will actually materialize. If an industrial consumer installs a DR technology, he becomes a DR operator. Since baseline consumption for each operator i is constant and baseline consumption is pre-paid, DR_i is formally equivalent to a generating unit with marginal costs equal to the gross value of consumption V_i. Following the revelation principle, we focus on direct mechanisms whereby the TSO asks potential DR operators to report their value of consumption V_i. We will show that the resulting level of DR installation is optimal, and all contracts are incentive-compatible. The timing, that we believe is consistent with reality, is as follows:

1. TSO presents a menu $MM(V)$ of payment to industrial consumers. Industrial consumer i can sign a contract. If he does, he invests in the DR technology and commits to shed load during pre-defined, publicly known periods.

2. Household demand realizes. Industrial DR may activate (i.e. operators agree to consume less than their desired unit demand), either prompted by high prices, or upon request from the TSO if a contract was signed.

4 Optimal contract

To keep the paper simple we only state our results, together with the intuition. The interested reader is referred to the appendix for formal proofs.

Proposition 2.1. *The maximization of social welfare requires that the cost of investment in DR technology is less than the net welfare gain of DR activation. To achieve optimal investment is suffices to pay each operator a lump-sum subsidy $MM(V_i)$ equal to the gross social value of DR activation, minus the energy market revenues of the operator.*

Proof. See Appendix A.1. □

This proposition derives directly from the fact the TSO is not biased against any agent. Hence it wants to make sure that any social-welfare improving investment materializes. For that, it suffices to ensure that investors fully receive the social value they create. In our case the TSO should deduct any revenues that may be derived from DR activation (in the present case, DR operators derive revenues from selling the energy they will not consume on the energy markets). We now describe in more detail the optimal payment to DR which opportunity cost of activation is low ($V_i < \bar{P}$), intermediate ($\bar{P} < V_i < V_h$) or high ($V_h < V_i$).

Remuneration of DR: Low value of consumption

A small opportunity cost of consumption $V_i < \bar{P}$ is the simplest and most intuitive case. Indeed, prices are efficient in the relevant range of DR activation, and DR behaves like traditional generation.

Corollary 2.1. *Assuming perfect availability of demand-response, and when the underlying opportunity cost of demand is below the price cap, capacity remuneration to demand-response should be same as for traditional generation.*

Proof. See Appendix A.2. □

Given that DR operators are price-takers, all existing DR with opportunity cost of activation lower than the price cap is activated when price is at the cap. This is precisely when a "missing money" is created. Hence, TSO payments should be independent of V_i as long as V_i is below the price cap. The intuition is that indeed, the gross social value of a DR service based on a higher opportunity cost demand is smaller than that of a service based on a smaller opportunity cost, since the service is called less often. However, this low social value service also generates less profit in the energy market. These two effects cancel out as long as the value of consumption is below the cap, and the missing money is the same for all services. Hence we recover the standard result that all types of capacity should receive the same payment, irrespective of their position on the load-shedding order (see eg. Cramton et al., 2013).[16]

Remuneration of DR: Intermediate value of consumption

This case is the one we argue has been overlooked in *all* current regulations. If V_i is greater than the price cap but lower than the system VoLL V_h, it may be socially optimal to activate DR_i when household demand is high. However, market prices are lower than the opportunity cost of activation of the DR operator. As a consequence, he never activates unless he signed a contract with the TSO.

Corollary 2.2. *Assuming perfect availability of demand-response, and when the underlying opportunity cost of demand is between the price cap and the system value of lost load, capacity remuneration to demand-response should be less than these of traditional generation.*

Proof. The proof, including the exact formulation of the optimal payment are provided in Appendix A.3. □

The key intuition behind this result is that not all DR is necessarily activated when price is at the cap and generates a missing money issue. While all price-responsive DR is activated (see previous case), some high-opportunity cost DR (V_i close to V_h) may not need to be activated for the TSO to maintain optimal service. Hence this high-cost DR creates less social value than the operators with opportunity cost only slightly above the price cap (who are more likely to be activated), and less payment for capacity is required to restore optimality.

[16]This is true for all services with equivalent availability at times of system stress, and same notice for activation.

Remuneration of DR: High value of consumption

When the opportunity cost of consumption is very high ($V_i > V_h$), and investments costs are non-negative, the optimal payment scheme excludes DR_i.

Corollary 2.3. *The optimal incentive scheme for DR gives a small bu strictly positive capacity payment to DR with opportunity cost higher than the system value of lost load. In equilibrium, no such DR enrolls.*

Proof. See Appendix A.4. □

The intuition of this result is rather straightforward. Since activation of DR with opportunity cost higher than the system value of lost load would decrease welfare, a TSO ensures the capacity payment is low enough so that no such DR enrolls. The payment is however strictly positive since the activation of such DR does yield a positive externality to consumers that will be served thanks to DR activation. However, this benefit is smaller than the private cost of DR. The TSO necessarily offers a payment that is smaller than the cost of activation of DR, and such capacity does not materialize.

Optimal de-rating factor

Figure 2.2 provides a visual representation of the main findings.[17] The main result of corollaries 1 to 3 is that payments to "upon-request" DR (activated when the price cap is binding) must be lower than price-responsive DR. For practical implementation, we introduce a novel de-rating factor $\alpha(V_i)$, that we argue should be applied to capacity payments for DR resources:

$$\alpha(V_i) = \begin{cases} 1, & \text{if } V_i < \bar{P} \\ \frac{MM(V_i)}{\overline{MM}}, & \text{if } \bar{P} \leq V_i \leq V_h \\ \frac{\underline{MM}}{\overline{MM}}, & \text{if } V_i > V_h \end{cases}$$

, with the missing money $\overline{MM} \geq MM(V_i) \geq \underline{MM}$ explicitly defined in Appendix A.2 (Equations A2.6,A2.7 and A2.8, respectively), and illustrated in Figure 2.2. We have that $\alpha(V_i) \leq 1$ for all values of V_i, meaning DR should never receive a higher reward than traditional generation, even if the underlying opportunity cost of consumption V_i is high. More precisely, a key property of this de-rating factor is that it is weakly decreasing in V_i and strictly so for intermediate value of consumption ($\bar{P} \leq V_i \leq V_h$). This de-rating

[17] I thank Richard Green for this idea of a representation

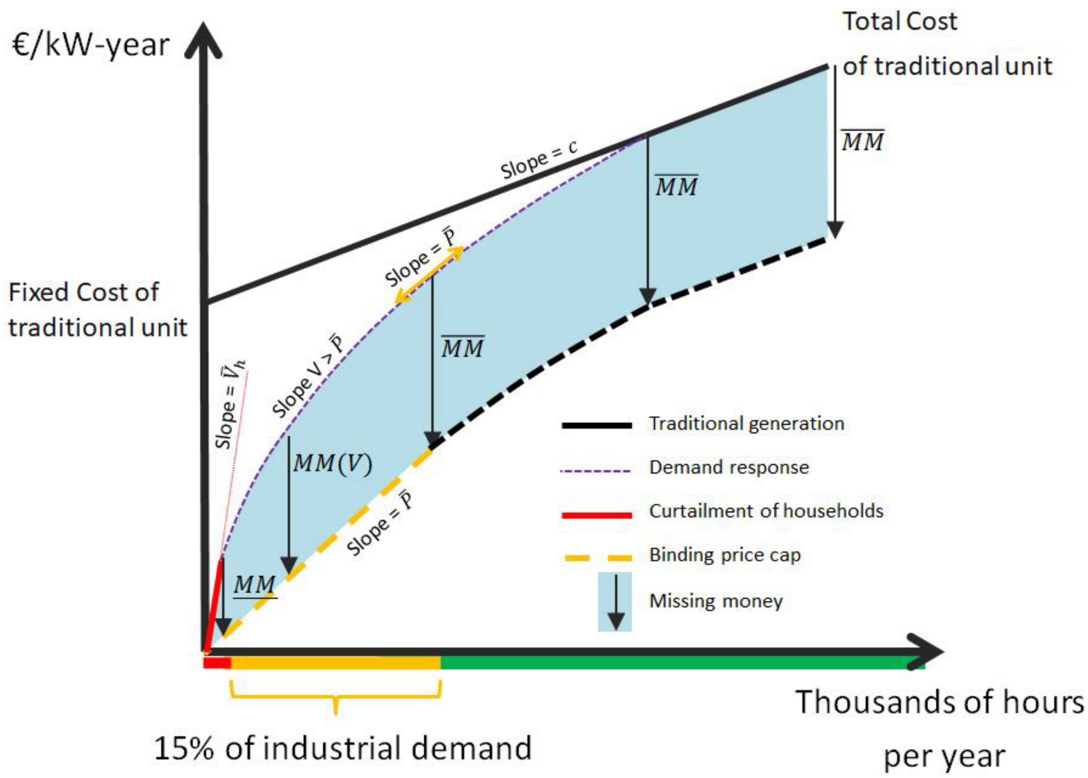


Figure 2.2: Screening curves when there is only one thermal technology with marginal costs $c < \bar{P} < V_h$. The missing money weakly decreases as the opportunity cost of activation of the DR technology increases. Optimality requires some high-opportunity cost industrial consumers to participate in DR

factor accounts for the fact a DR resource may not always be activated when prices are at the cap, in which case it suffers less from the missing money problem.

Discussion of the findings

We acknowledge that an actual implementation of these payments would require a much finer modelling of power systems (esp. demand and DR implementation costs). Indeed, an important assumption for the TSO to offer first-best implementing contracts is that it knows the distribution of the characteristics (fixed and variable costs of DR-enabling technology) in the population of potential DR operators. As noted in Wilson (1989), this assumption may be reasonable if the distribution is stable over time, as consumers reveal their preferences through their past selection of contracts. Even absent such contracts, some estimates of the distribution of V_i may be inferred from the analysis of added value in industrial sectors (see e.g. London Economics, 2013). Estimates of fixed costs of DR in the industrial sector are available in Department for Energy and Climate Change and Ofgem (2011) or Kreuder et al. (2013). Despite being of significant practical relevance, numerical applications are left for future research.

Appendix B shows that the contracts exhibited in this section are incentive-compatible, i.e. a potential operator with opportunity cost V_i asked to choose a contract $MM(\tilde{v})$, indeed will choose to report $\tilde{v} = V_i$. Note also that this menu does not require DR operators to actually see and react to prices in real time. In the spirit of the priority service literature, they just need to know in which states of the world they will be required to shed load, given the opportunity cost $\tilde{v}$ they report.

5 Case studies

The intense debate on FERC's order 745 (see Chen and Kleit, 2016) has highlighted many misconceptions on the values of DR and what sort of incentives and monitoring it should receive. In parallel, CRMs are also subject to active debates, starting from questioning whether it is state aid or not. This section sets itself the ambitious goal to clarify where we stand, when it comes to DR participation to CRMs. Indeed, while the previous section exposed an optimal capacity payment to DR, it would now be useful to compare it to designs currently in place. The Smart Energy Demand Coalition (2015a) provides a very thorough overview of DR designs in place in various countries, highlighting their diversity. Warren (2015) provides insights on what features make them successful or not. Fortunately, in our simplified setting that focuses on the *capacity* value of DR, all of these designs can be reduced to either of two designs: i.e. no capacity payment at all, or full capacity payment ($\overline{MM}$ in the present model). This section compares these payments with the optimal one.

Benchmark: optimal payment to DR

Figure 2.3 shows the optimal payment to DR as a function of the value of consumption V_i of the operators. The thick dotted line shows the opportunity costs of offering DR, once fixed costs of DR are paid and sunk. No DR with $V_i > V_h$ and positive fixed costs sign a DR contract. Entry of DR with $V_i < V_h$ depends on fixed costs of the DR-enabling technology.

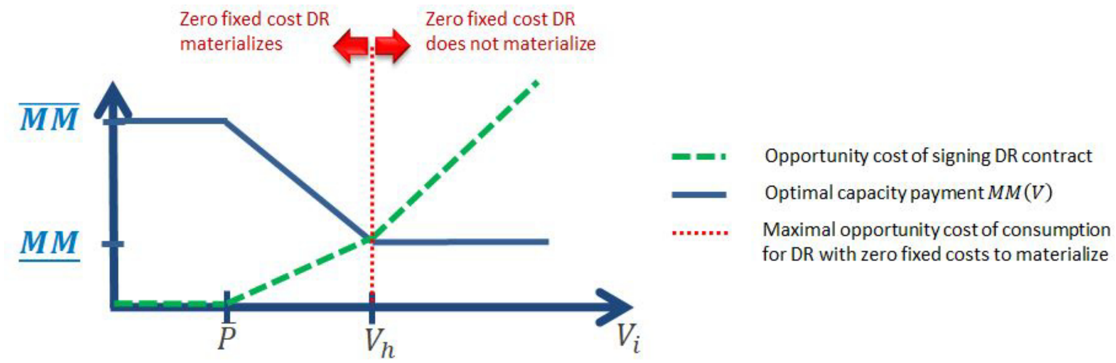


Figure 2.3: Optimal payment to DR and opportunity cost thereof, as a function of the value of consumption V_i. The dotted vertical line is the maximum value V_i for an industrial consumer to install a DR technology when there are no fixed costs ($r_i = 0$).

Case 1: No capacity payment to DR

This corresponds to markets where there is no CRM (Netherlands, Denmark, Central Europe, ERCOT...), or where DR does not receive any remuneration for capacity. Even though there seems to be an agreement that DR should be remunerated for its contribution to adequacy (see Cramton et al., 2013), it is often excluded in practice. This exclusion can be *de jure* as in Italy or Spain (see Smart Energy Demand Coalition, 2015a) or *de facto* if eligibility criteria are too stringent –see European Commission (2016) for an interesting discussion on these criteria.

If there is no payment to DR at all, only those operators who can survive with energy market revenues offer DR. This is more restrictive than the optimal entry condition exposed in Proposition 1, that allows for a positive lump-sum payment, in addition to market revenues. No DR with underlying opportunity cost greater than the price cap enrolls, despite their enrollment being optimal if fixed costs are small enough. Thus, echoing the existing literature we find that there is not enough entry in the DR business if DR is denied a remuneration for capacity.

Case 2 : Full capacity payment

Now, suppose that DR capacity qualifies for capacity remuneration on the basis of **technical availability** at times of scarcity, as is the case in PJM, France, or the UK. DR with value higher than the price cap is activated **upon request** from the TSO. Figure 2.4 shows there is excess payment: some DR with $V_i > V_h$ sign a DR contract so as to cash in the full capacity payment in exchange of a very low probability of activation. This enrollment is clearly suboptimal.

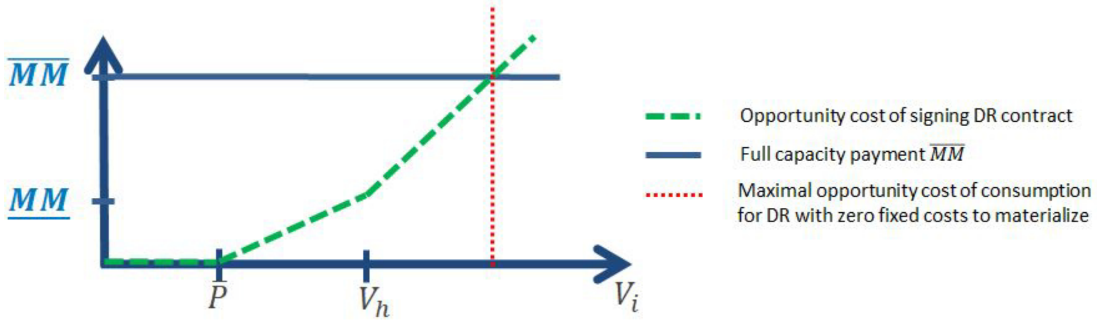


Figure 2.4: Full capacity payment to DR. The cutoff value for installation of DR technologies is shifted to the right compared to the optimal cutoff.

Rewarding DR on the same basis as capacity – or equivalently allowing DR participation to capacity auctions without a de-rating of payments specifically related to activation periods– results in excessive payment to DR and excess entry of high-opportunity cost DR. Similarly, an implicit participation whereby consumers offering non-price responsive DR are exempt from any CRM contribution may constitute a hidden subsidy.

6 Conclusion

The integration of demand response in capacity mechanisms remains a key regulatory challenge. In this paper, we have assumed that the presence of a price cap leads regulators to provide additional remuneration for capacity. We observed that a side effect of this price cap is that prices sometimes fail to provide adequate information for DR activation. As a consequence, we showed analytically that even absent asymmetry of information on volumes (i.e. what would have been consumed by operator i absent a DR technology is public information), current designs fail to screen DR technologies and dispatch them optimally. In particular, we find that it is crucial to know whether DR will activate *before* the market price hits the cap or *when* they hit it. In the former case, DR should receive the same capacity payment as traditional generation. However, if a DR operator does not commit to activating at a price strictly lower than the cap but instead awaits a request from the TSO, it should receive **only a portion** of the capacity payment. All capacity remuneration mechanisms currently in place fail to account for this phenomena. As a correction, we propose to de-rate payment to DR capacity and use a stylized setting to derive the de-rating factor explicitly. It should decrease as the DR operator's position in the activation order increases.

Potential extensions of this work include allowing for time-inconsistency of the opportunity cost of consumption and addressing the case when the regulator's objective function is biased against DR operators. In that case the TSO (i.e. the Principal) needs to leave an information rent to "good" type agents (in our case, low-opportunity cost operators), and distort activation periods. Also, we assumed that the Principal was unbiased, and could make transfers in a costless manner. Relaxing these assumptions would lead to less DR adoption. Finally, allowing for asymmetry of information on load-shedding volume availability would be very useful, albeit analytically much more complex.

Bibliography

Aalami, H. A., Moghaddam, M. P., and Yousefi, G. R. (2010). Demand response modeling considering Interruptible/Curtailable loads and capacity market programs. *Applied Energy*, 87:243–250.

Adib, P., Schubert, E., and Oren, S. (2008). *Chapter 9: Resource Adequacy: Alternate Perspectives and Divergent Paths.*

Albadi, M. H. and El-Saadany, E. F. (2008). A summary of demand response in electricity markets.

Astier, N. and Léautier, T.-O. (2016). Demand Response: Smart Market Designs for Smart Consumers. *working paper.*

Batlle, C. and Rodilla, P. (2010). A critical assessment of the different approaches aimed to secure electricity generation supply. *Energy Policy*, 38(11):7169–7179.

Behrangrad, M. (2015). A review of demand side management business models in the electricity market. *Renewable and Sustainable Energy Reviews*, 47:270–283.

Borenstein, S. (2002). The Trouble With Electricity Markets: Understanding California's Restructuring Disaster. *Journal of Economic Perspectives*, 16:191–211.

Borenstein, S. (2005). The long-run efficiency of real-time electricity pricing. *Energy Journal*, 26:93–116.

Borenstein, S., Bushnell, J. B., and Wolak, F. A. (2002). Measuring market inefficiencies in California's restructured wholesale electricity market. *American Economic Review*, 92:1376–1405.

Borenstein, S. and Holland, S. (2003). On the efficiency of competitive electricity markets with time-invariant retail prices. *The Rand Journal of Economics*, 36:469–493.

Brophy Haney, a., Jamasb, T., and Pollitt, M. G. (2009). Smart Metering and Electricity Demand: Technology, Economics and International Experience. *Policy*, 44:1–72.

Bushnell, J., Hobbs, B. F., and Wolak, F. A. (2009). When It Comes to Demand Response, Is FERC Its Own Worst Enemy? *Electricity Journal*, 22:9–18.

Caramanis, M., Bohn, R., and Schweppe, F. (1982). Optimal Spot Pricing: Practice and Theory. *IEEE Power Engineering Review*, PER-2:42.

Chao, H.-p. (2010). Price-Responsive Demand Management for a Smart Grid World. *The Electricity Journal*, 23:7–20.

Chao, H.-p. (2012). Competitive electricity markets with consumer subscription service in a smart grid. *Journal of Regulatory Economics*, 41:155–180.

Chao, H.-p., Oren, S. S., Smith, S. A., and Wilson, R. B. (1986). Multilevel demand subscription pricing for electric power. *Energy Economics*, 8:199–217.

Chao, H.-P. and Wilson, R. (1987). Priority Service: Pricing, Investment, and Market Organization. *The American Economic Review*, 77:899–916.

Chen, X. and Kleit, A. N. (2016). Money for Nothing ? Why FERC Order 745 Should have Died. 37(2):201–222.

Cramton, P., Ockenfels, A., and Stoft, S. (2013). Capacity Market Fundamentals. *Economics of Energy & Environmental Policy*, 2:1–21.

Cramton, P. and Stoft, S. (2006). The convergence of market designs for adequate generating capacity with special attention to the CAISO's resource adequacy problem. *Berkeley, California, White Paper for the Electricity Oversight Board.*

De Vries, L. J. (2007). Generation adequacy: Helping the market do its job. *Utilities Policy*, 15(1):20–35.

Department for Energy and Climate Change and Ofgem (2011). Smart meter rollout for the small and medium non-domestic sector (GB). Impact Assessment. Final. Technical report.

Doucet, J. A. and Roland, M. (1993). Efficient Self-Rationing of Electricity Revisited. *Journal of Regulatory Economics*, 5:91–100.

Economie.fgov.be (2015). Plan de délestage en cas de pénurie d'électricité.

ENTSO-E (2015). Market Design for Demand Side Response. Technical report.

European Commission (2016). Interim Report of the Sector Inquiry on Capacity Mechanisms. Technical report.

Faruqui, A. and George, S. (2005). Quantifying customer response to dynamic pricing. *Electricity Journal*, 18:53–63.

Faruqui, A., Harris, D., and Hledik, R. (2009). Unlocking the €53 Billion Savings from Smart Meters in the EU. Technical report.

Faruqui, A., Hledik, R., Newell, S., and Pfeifenberger, H. (2007). The Power of 5 Percent. *Electricity Journal*, 20:68–77.

Faruqui, A. and Sergici, S. (2010). Household response to dynamic pricing of electricity: A survey of 15 experiments.

Federal Energy Regulatory Commission (2015). Assessment of Demand Response & Advanced Metering. Technical report.

Hogan, W. (2009). "Providing Incentives for Efficient demand Response", Prepared for Electric Power Supply Association, Comments on PJM Demand Response Proposals. *FERC Docket N° EL09-68-000.*

Joskow, P. (2013). Symposium on 'Capacity Markets'. *Economics of Energy & Environmental Policy.*

Joskow, P. and Tirole, J. (2007). Reliability and competitive electricity markets. *The RAND Journal of Economics*, 38:60–84.

Kreuder, L., Gruber, A., and Von Roon, S. (2013). Quantifying the costs of Demand Response for industrial businesses. In *IECON Proceedings (Industrial Electronics Conference)*, pages 8046–8051.

Léautier, T. O. (2014). Is mandating "smart meters" smart? *Energy Journal*, 35:135–157.

Léautier, T.-O. (2016). The visible hand: ensuring optimal investment in electric power generation. *Energy Journal*, 37(2):89–109.

London Economics (2013). The Value of Lost Load (VoLL) for Electricity in Great Britain Final report for OFGEM and DECC. Technical Report July.

Marchand, M. G. (1974). Priority Pricing. *Management Science*, 20:1131–1140.

National Grid (2016). Capacity Market Auction Guidelines 2015. Technical Report June 2015.

National Grid (2017). National Grid EMR Electricity Capacity Report. (June):1–109.

Newbery, D. (2016). Missing money and missing markets: Reliability, capacity auctions and interconnectors. *Energy Policy*, 94:401–410.

Panzar, B. J. C. and Sibley, D. S. (1978). Public Utility Pricing under Risk : The Case of Self-Rationing. 68(5):888–895.

Rious, V., Roques, F., and Perez, Y. (2012). Which electricity market design to encourage the development of demand response? *Robert Schuman Centre for Advanced Studies, EUI RSCAS Working Paper*, 12.

Schweppe, F. C. (1988). Management of a spot price based energy marketplace. *Energy Policy*, 16:359–368.

Smart Energy Demand Coalition (2015a). Enabling independent aggregation in the European electricity markets. Technical Report February.

Smart Energy Demand Coalition (2015b). Mapping Demand Response in Europe Today Mapping Demand Response in Europe Today. Technical report.

Steen, D., Anh Tuan, L., and Bertling, L. (2012). Price-Based Demand-Side Management For Reducing Peak Demand In Electrical Distribution Systems–With Examples From Gothenburg.

Strbac, G. (2008). Demand side management: Benefits and challenges. *Energy Policy*, 36:4419–4426.

US Department of Energy (2006). Benefits of Demand Response in Electricity Markets and Recommendations for Achieving Them. *U.S. Department of Energy*, page 122.

Warren, P. (2015). Demand-Side Management Policy : Mechanisms for Success and Failure. *Doctoral thesis, UCL (University College London).*

Wilson, R. (1989). Efficient and Competitive Rationing. *Econometrica*, 57:1–40.

Woo, C.-k. (1990). Efficient Electricity Pricing with Self-Rationing. 81:69–81.

A Proofs of Proposition 1 and corollaries

Household demand is denoted l, with probability density function $f(l)$. On top of the notations defined in the main text and to simplify formulas, we define $V_f(l)$ the cost that is avoided by activation of a unit of DR, in state of the world l. $V_f(l)$ depends on the realized enrollment in DR. The set of pre-defined periods of activation for DR with underlying cost of consumption V is denoted L_V and agent i's fixed costs of investment in a DR-enabling technology is r_i.

- if there is excess capacity (all desired demand is fully covered with traditional capacity): $V_f(l) = c(l)$, with $c(l)$ the marginal cost of generation. Contrary to the illustration in Figure 3.7, we assume for simplicity that there is only one technology with constant marginal costs: $c(l) = c$.
- if TSO resorts to random curtailment: $V_f(l) = V_h$
- otherwise, some but not all DR (either price-responsive or contracted) is activated: $V_f(l) = max\{V_i \,/\, DR_i \, is \, activated\}$

A.1 Proof of Proposition 1

Take a DR operator i, whose value of consumption is $V_i \in [0, \infty[$. V_i is the opportunity cost of DR activation, incurred by agent i. The overall social cost of activating such DR in states of the world $l \in L_V$ is $C(V) = \int_{L_V} V f(l) dl$. The gross social benefit $B(V_i)$ of activating this DR, is driven by the value of consumption of the first unserved consumer: $B(V_i) = \int_{L_{V_i}} V_f(l) f(l) dl$, who would be served thanks to this activation. Thus, the net social benefit is :

$$W(V_i) = B(V_i) - C(V_i) = \int_{L_{V_i}} (V_f(l) - V_i) f(l) dl \qquad \text{(A2.1)}$$

Hence, once the DR technology is installed it is optimal to activate DR i if and only if $V_i < V_f(l)$. We thus have that $L_{V_i} = \{l, V_f(l) > V_i\}$. It follows that if $V' > V$ then $L_{V'} \subset L_V$ and $W(V') < W(V)$. That is, the higher V is, the less frequent the activation is, and the smaller the net social benefit of such DR is. This intuition is the key driver of our main results.

To obtain optimal investment in DR in equilibrium, the TSO wants to make sure

DR operator i receives $B(V_i)$, such that there is entry if and only if

$$\begin{aligned} r_i + C(V_i) < B(V_i) = W(V_i) + C(V_i) \\ \Leftrightarrow r_i < W(V_i) \end{aligned} \tag{A2.2}$$

This condition ensures that there is investment if and only if the investment cost is smaller than the net social benefit. Note that we allow the DR operator i to sell the foregone consumption at energy market prices. This means DR operators are allowed to be relatively sophisticated and technically act as generators in the market for energy. Therefore the TSO only needs to pay the difference between the gross social value and these market revenues, henceforth denoted $MM(V_i)$:

$$MM(V_i) = B(V_i) - EM(V_i), \tag{A2.3}$$

where $EM(V_i)$ is the energy market revenues made by an operator i with underlying value of consumption V_i. For ease of exposition, the next subsections study the cases with DR opportunity costs respectively below the price cap $\bar{P}$, between $\bar{P}$ and the system value of lost load V_h and above V_h. Note also that if the price cap is set at the VoLL ($\bar{P} = V_h$), there is no need for a payment at all: in our simple setting this case corresponds to an efficient pricing paradigm, and no CRM is needed at all.

A.2 Proof of Corollary 1

To ease notations hereafter, the subscript i is omitted. Even though operators might pick up any contract, appendix B shows they report their opportunity cost truthfully. We slightly abuse notations in the integration domain by denoting "$p < (=)\bar{P}$" the states of the world when the energy market price is below (at) the price cap.

As noted, DR operators may be allowed to re-sell their load-reduction in the energy market:

$$EM(V) = \int_{L_V \cap p<\bar{P}} V_f(l) f(l) dl + \int_{L_V \cap p=\bar{P}} \bar{P} f(l) dl, \tag{A2.4}$$

where the first term represents revenues made when the price is set by the value of the first unserved consumer (meaning prices are efficient), and the second term is revenues when the price is at the cap. We also decompose the gross utility of activation:

$$B(V) = \int_{L_V \cap p<\bar{P}} V_f(l) f(l) dl + \int_{L_V \cap p=\bar{P}} V_f(l) f(l) dl \tag{A2.5}$$

The "missing money" to be paid to DR operators is therefore:

$$\begin{aligned} MM(V) &= B(V) - EM(V) \\ &= \int_{L_V \cap p=\bar{P}} (V_f(l) - \bar{P}) f(l) dl \equiv \overline{MM} \end{aligned} \tag{A2.6}$$

Note that the capacity payment to DR is the same as for traditional generation, and does not depend on V since the set $\{L_V \cap p = \bar{P}\}$ is the same for all $V < \bar{P}$.

A.3 Proof of Corollary 2

As discussed earlier, optimality requires that the TSO activates DR only if $p = \bar{P}$ i.e. $\{L_V \cap p = \bar{P}\} = \{L_V\}$. The TSO needs to give the missing money:

$$\begin{aligned} MM(V) &= B(V) - EM(V) \\ &= \int_{L_V} \bar{V}_f(l) dl - \int_{L_V} \bar{P} f(l) dl \\ &= \int_{L_V} (V_f(l) - \bar{P}) f(l) dl < \overline{MM} \end{aligned} \tag{A2.7}$$

Note that the states of the world with activation is of smaller measure as V increases: $V' > V > \bar{P} \Rightarrow L_{V'} \subset L_V$. Hence the payment $MM(V)$ is decreasing in V on segment $[\bar{P}, V_h]$. The intuition is that a marginal increase in $V \in [\bar{P}, V_h]$ would result in a gross social welfare loss of $V \cdot f\left(V_f^{-1}(V)\right)$, but in a loss in energy revenues of only $\bar{P} \cdot f\left(V_f^{-1}(V)\right)$. Thus, the compensation of the TSO should decrease as V increases.

A.4 Proof of Corollary 3

Assume that the TSO allows DR with very high opportunity cost to activate in states of the world L_V, just before resorting to random curtailment of households:

$$\begin{aligned} MM(V) &= B(V) - EM(V) \\ &= \int_{L_V} (V_f(l) - \bar{P}) f(l) dl \\ &= \int_{L_V} (V_h - \bar{P}) f(l) dl \equiv \underline{MM} \end{aligned} \tag{A2.8}$$

There will be entry if and only if

$$r_i(V) < W(V) = \int_{L_V} (V_f(l) - V) f(l) dl$$
$$\leq \int_{L_V} (V_h - V) f(l) dl < 0$$

Hence the TSO will not activate this technology (i.e. $\{L_V\} = \emptyset$) unless it *creates* some value, through other channels. This would be translated in the present model by a negative fixed cost r_i.

B Proof of incentive compatibility

Denote by $R(V, \tilde{v})$ the expected revenues of a potential DR operator with opportunity cost V, when it enrolls in a DR scheme and reports $\tilde{v}$.

B.1 case $V < \bar{P}$

We can assume away that $\tilde{v} > \bar{P}$. Indeed, the TSO payment is less, and DR is not activated during some profitable load-shedding events. An operator i will have to pay r and gets $\overline{MM}$, whatever the opportunity cost $\tilde{v} \in [0, \bar{P}]$ he announces. His revenues can be decomposed into a payment for capacity, market revenues when prices are below the cap, and market revenues when prices are at the cap:

$$R(V, \tilde{v}) = \overline{MM} + \int_{L_{\tilde{v}} \cap p < \bar{P}} (V_f(l) - V) f(l) dl + \int_{L_{\tilde{v}} \cap p = \bar{P}} (\bar{P} - V) f(l) dl \quad \text{(A2.9)}$$

It is easy to see that revenue is maximized when:

$$L_{\tilde{v}} = \{l / V_f(l) > V\} = L_V \quad \text{(A2.10)}$$

Hence a potential DR operator reports her opportunity cost truthfully.

B.2 case $\bar{P} \leq V < V_h$

Assume that operator i reports $\tilde{v} \in [\bar{P}, V_h]$. It gets both a payment for capacity $MM(\tilde{v})$ (which expression is given by equation A2.7)and some energy market revenues:

$$\begin{aligned} R(V,\tilde{v}) =& MM(\tilde{v}) + \int_{L_{\tilde{v}} \cap p=\bar{P}} (\bar{P} - V) f(l) dl \\ =& \int_{L_{\tilde{v}} \cap p=\bar{P}} (V_f(l) - V) f(l) dl \end{aligned} \tag{A2.11}$$

Again, it chooses optimally

$$L_{\tilde{v}} = \{l / V_f(l) > V\} = L_V \tag{A2.12}$$

If it reports $\tilde{v} \in [0, \bar{P}]$, it gets:

$$\begin{aligned} R(V,\tilde{v}) =& \overline{MM} + \int_{L_{\tilde{v}} \cap p<\bar{P}} (V_f(l) - V) f(l) dl \\ &+ \int_{L_{\tilde{v}} \cap p=\bar{P}} (\bar{P} - V) f(l) dl \\ =& \int_{L_{\tilde{v}} \cap p<\bar{P}} (V_f(l) - V) f(l) dl \\ &+ \int_{L_{\tilde{v}} \cap p=\bar{P}} (V_f(l) - V) f(l) dl \end{aligned} \tag{A2.13}$$

The second term is at best what it would get if it would report truthfully. The first term is negative as $\bar{P} \leq V$. Therefore reporting $\tilde{v} \in [0, \bar{P}]$ is not rational. If it reports $\tilde{v} \in [V_h, \infty[$, it gets:

$$\begin{aligned} R(V_i,\tilde{v}) =& \underline{MM} + \int_{L_{\tilde{v}} \cap p=\bar{P}} (\bar{P} - V) f(l) dl \\ &= \int_{L_{\tilde{v}} \cap p=\bar{P}} (V_h - V) f(l) dl \\ &= R(V,V) - \int_{L_V \cap p=\bar{P} \cap V_f(l)<V_h} (V_f(l) - V) f(l) dl && \text{(A2.14)} \\ &< R(V,V) && \text{(A2.15)} \end{aligned}$$

Thus, operator i reports truthfully.

B.3 case $V_h \leq V$

Assume operator i reports $\tilde{v} \in [\bar{P}, V_h]$ to get higher payment for capacity. The revenues it makes is:

$$R(V, \tilde{v}) = MM(\tilde{v}) + \int_{L_{\tilde{v}} \cap p = \bar{P}} (\bar{P} - V) f(l) dl$$
$$= \int_{L_{\tilde{v}} \cap p = \bar{P}} (V_f - V) f(l) dl < 0 \tag{A2.16}$$

Hence, it makes negative profits: there is no entry, as optimality requires. Similarly, if it reports $\tilde{v} \in [0, \bar{P}]$ it gets:

$$R(V, \tilde{v}) = MM(\tilde{v}) + \int_{L_{\tilde{v}} \cap p = \bar{P}} (\bar{P} - V) f(l) dl$$
$$= \int_{L_{\tilde{v}} \cap p = \bar{P}} (V_f - V) f(l) dl < 0 \tag{A2.17}$$

Thus, operator i reports truthfully and does not enroll in a DR scheme.

Part II

Consumer choices in the digital economy

Chapter 3

Digital platforms: does promoting competitors promote competition?

About this chapter

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A related paper applies the model to energy communities. Owing to its preliminary stage, this paper is not included in the present thesis.

Abstract

Digital platforms frequently refer their users to content of competitors. We show that these references induce a business-sharing effect that may relax competition for users, resulting in lower quality of content. More surprisingly, user surplus may also decrease as the quality effect may overwhelm the positive effect of accessing more content. In the media sector, which is our lead application, newspapers delegate the referencing activity to independent third parties. We show that the fees charged by the third parties mitigate the anti-competitive effect while preserving the diversity effect. We finally show that competition among third parties generates the fee structure that maximizes user surplus. In that case, interplatform references promote both the diversity and quality of content of digital industries. While regulators actively seek tools to promote the diversity and quality of content in digital industries, our results show that scrutiny over the inter-platform referencing business provides new and possibly powerful instruments for regulation.

Keywords-Two-sided markets, Platforms, Tacit collusion, Entry, Quality, Advertising

1 Introduction

Mutual referencing between competitors is prevalent in digital markets. When searching for flight tickets, car rentals, hotel rooms or more generally information using dedicated websites, users are regularly offered the option to also visit the content of direct competitors. For example, CNN.com may show links to the New York Times. Tripadvisor offers users to compare their hotel results with those of Expedia.[1] These references facilitate the navigation across competitors. At first sight, this seems to intensify competition between competing platforms. However, the sharing of users may be anti-competitive. The present paper models platforms' choice of engaging in interplatform referencing and shows this may negatively affect quality, and both user and social surplus. We provide regulatory advice on how to tackle this issue.

Although our model may apply to any online intermediation platform, we primarily focus on free online newspapers. This industry is of particular interest because it may promote or discourage ideological diversity and influence political processes (Gentzkow and Shapiro (2010); Allcott and Gentzkow (2017); Cage (2017)). It is therefore under the

[1]See Appendix A.1 for familiar examples of such references between competitors.

constant scrutiny of regulators (state aids, specific regimes of value-added tax, antitrust and mergers). Despite intense competition in the media industry,[2] this paper observes that news websites routinely refer readers to their own competitors through hyperlinks. We refer to such links as "sponsored" content. On the contrary "advertisement" directs readers to non-competitors. Sponsored content usually takes the form of embedded links (see Figure 3.1). The frame that displays them is often located on the side or at the bottom of articles, and titled "content you may like", "best stories for you" or "also on the web". Although these recommendations have been widely criticized for displaying deceptive content, some of the links do refer to high-quality competitors: in Section 3, we use data on the major French news websites to show that a large share of the sponsored content leads to high-quality competitors of the initial news outlet. Recent initiatives show the referencing of competitors is set to spread further in the near future.[3] Contrary to other digital platforms, who bilaterally manage references, newspapers delegate the selection of external content to independent third parties. We call these third parties "go-betweens". These go-betweens reach billions of web users each month and make billions of dollars in revenue by charging fees for the clicks they generate.[4]

In a simple theoretical setting, we analyze the effect of interplatform referencing on competition between two digital platforms. We show that go-betweens and in particular the fees they charge have strong implications for newspapers' quality provision. The platforms gather two types of users. On one side are web users, individuals who are primarily interested in the quality of content available on the platform. Quality could represent the trustworthiness or clarity of information, the user-friendliness of the interface, the presence of ancillary services, etc. On the other side of the platform are advertisers, private firms who are willing to sell a service or a good to individuals. They are primarily interested in interacting with web users and are willing to pay the platform for these interactions. The go-betweens allow users to "roam" directly to some external content, without actively searching for it. Some users would, absent a go-between, visit only one platform: the go-between induces an expansion of the overall number of pages they view. The sponsor platforms pay a sponsoring fee to the go-between, in exchange for each view obtained through sponsored links. The go-between pays a (typically smaller) publisher fee to the platforms that display the sponsored links.

[2]See for example Gentzkow et al. (2011), Drago et al. (2014)

[3]In 2018, the content recommendation company Outbrain launched a premium product, "Sphere", that directs readers of selected newspapers exclusively to high-quality competitors that are also members of the sphere.

[4]See Section 3 and Appendix A.2 for more detail about go-betweens in the media sector and their business model.

Our first result is that interplatform references may relax competition as well as reduce the equilibrium quality in both platforms. The main intuition is that platforms compete to become a user's "anchor" platform, which is the platform where a user starts searching for information. However, references allow users to also visit their platform of second choice. Hence, with references, the loss of an anchored user induces less of a revenue loss to the platforms, because that user becomes a "roamer". Therefore, the competition for anchored users becomes less fierce after the introduction of references and quality decreases. This decrease in quality affects not only the content to which users roam, but the whole corpus of content: user surplus also decreases, as the negative quality effect overwhelms the positive effect of accessing more content.

Our second set of results concerns the reference fees. We show that high reference fees restore competition. The intuition is that the sponsoring fees increase platforms' cost of attracting roamers, while the publisher fees increase platforms' returns to competing for anchored users. Hence, with high fees platforms have a stronger incentive to attract anchored users, instead of paying a large fee for sponsored links and attract roamers. If fees are sufficiently high, quality can be restored to its level without references. In that case, references increase user surplus.

We show that reference fees are suboptimally low when platforms manage references by themselves. Delegating the sponsoring activity to a third party monopoly, the go-between, only partially solves the issue. Importantly, we find that efficiently high fees are achieved when there is sufficient competition among several go-betweens and when there are no exclusive contracts. The reason is that sponsors can typically use several go-betweens. Therefore, they use a go-between as soon as its sponsor fees are just below their willingness to pay. Conversely, publishers tend to use only one go-between. Hence they join the go-between that offers the highest publisher fees, conditional on sponsors having joined this go-between. Therefore, when the third parties use simple price instruments, competition among several go-betweens results in fees being set at the maximum feasible level.[5]

Our policy recommendation is that regulators should be wary of markets where platforms refer users to additional external content, when references come with no, or low fees. This means users may have access to more content, but of a lower quality. Some platforms, for example flight or hotel search engines, manage references themselves. Regulators may want to ensure these are delegated to third parties, the "go-betweens",

[5]Another possible solution would be to regulate the fees, as was done for call termination in the telecommunication industry.

as is already exemplified in the newspaper industry. Further, they should ensure that there is sufficient competition among these go-betweens, so that reference fees reach a level that encourages competition.

Our main contributions are the following. First, we show empirically that digital platforms actively refer their users to competitors. Second, we show that roaming is fundamentally different from multi-homing. Exploiting this, our results strongly contrast with the premise that reducing search and visit costs, and providing users with more information promotes competition. For the first time, we study the fact that the references may be intermediated and come at a fee. We show that the fee structure has important implications for the competition between platforms.

The remainder of the paper is organized as follows. Section 2 reviews the literature. Section 3 provides empirical evidence of the pervasiveness of interplatform referencing in the online news industry. It shows that the referenced content is likely to induce an expansion, rather than a substitution of demand. Section 4 develops our base model and benchmark without a go-between. Section 5 introduces the go-between. It shows that the presence of nonoverlapping content can make interplatform referencing profitable to both platforms involved in the relationship. However, references may dampen platforms' incentive to produce quality when reference fees are low. Section 6 shows this may induce a loss in user surplus, especially for users with strong preferences. Go-betweens, users, platforms and the social planner have conflicting interests regarding the setting of fees. Competition among go-betweens generates the set of fees that strengthens competition. In Section 7 we present several extensions of the base model. Section 8 concludes.

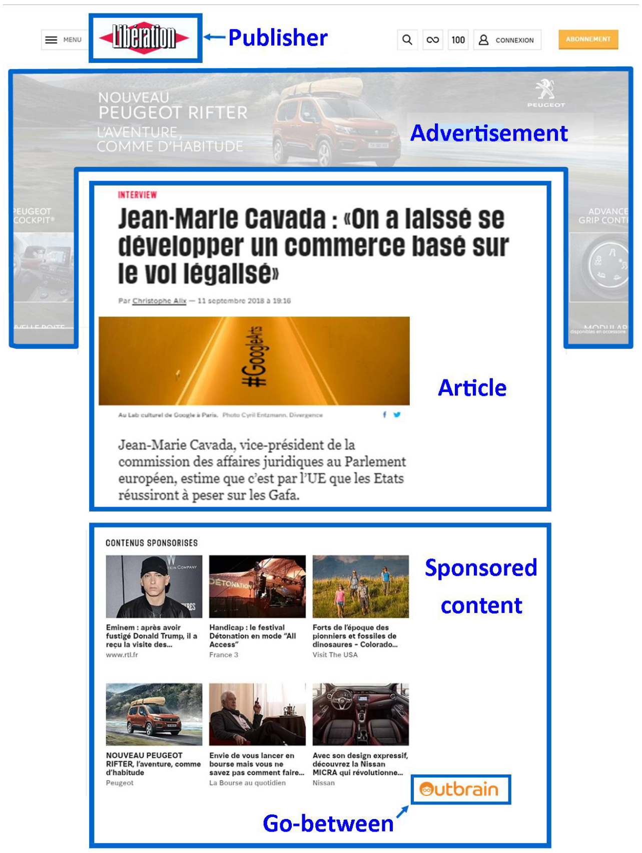


Figure 3.1: An article from the French online newspaper Libération, published and accessed on September 12, 2018.

2 Literature review

This article relates to at least three streams of literature. First, its formalism is one of two-sided markets. The topic has gained much interest since the early 2000s and the progress in information and communication technologies. Seminal papers include Rochet and Tirole (2003), Caillaud and Jullien (2003), Parker and Van Alstyne (2005), Armstrong (2006), and Hagiu (2006). Of this extensive literature, the discussion on multi-homing is particularly relevant to the present paper. A key distinction, often taken as an assumption, is whether consumers single-home (i.e. they participate in at most one platform), or multi-home. The present paper allows for a somewhat intermediate situation. Users first choose their anchor site, which is their main source of information. Hence the decision of where to anchor remains a single-homing decision.

Then, interplatform references incite them to sometimes roam to the content of a competing website, directly from their anchor. A key distinction with the literature on multi-homing is that roaming is controlled and agreed upon by all parties: the platforms (whether they publish external references, or sponsor content), the go-between and the users. Armstrong and Wright (2007) expose how multi-homing may arise, and show that platforms would have an incentive to sign exclusive contracts with multi-homers. The authors show that multi-homing increases prices to multi-homers. This finding is coherent with the effect we describe here, but with a very different motivation: in the present paper, platforms still compete head-to-head for anchored users. However, the incremental value of anchored users relative to roamers decreases with interplatform references. In turn, this softens competition. In the advertisement literature, Ambrus et al. (2016) and Athey et al. (2012) show that competition for attention means multi-homers may be less valuable to advertisers. Including this effect may dampen the magnitude of our results without invalidating them.

The paper also connects to the literature on network formation. Ma (2010) and Kozinets (2008) explain network formation by a motivation to create "virtual shopping malls" that guide users through a net of outlets. The empirical work of Ma (2010) describes how developers link to one another. He finds that limiting links may increase overall viewership substantially. Links are, however, motivated by a "promote-the-promoter" effect, whereby content producers strive to secure a central part of the network users are navigating. In the present paper, links are motivated by a need to access diverse content, and the appeal of a remuneration per click. Katona and Sarvary (2008) were among the first to analyze network formation on the web as directed graphs. However, there is no consumer heterogeneity and links are established without considerations of whether they direct to competitors, which is a key element of our paper. No analysis of the impact of links on quality or vice-versa is performed. Mayzlin and Yoganarasimhan (2012) study a blogger's strategic decision to link to a competitor's blog. Their work focuses on capturing bloggers' local link formation decisions. It does not attempt to analyze the system-level consequences of such decisions on network structure or content quality. Closest to our paper is Dellarocas et al. (2013). The authors examine interdependent content and link formation decisions between websites. They find that in the case of homogeneous costs, the only pure equilibrium consists of either no linking or websites separating into two groups. One creates quality content. The other one invests in lower quality and merely directs his readers to blogs of the first group. In doing so, they take advantage of "shallow" readers only interested in the summary provided by the inefficient outlets to which they have been randomly assigned. This random assignment is realistic in the case of blogs, but perhaps less so in the case of generalist news outlets or search engines: here we assume that users are reasonably well informed about the variety of platforms at their disposal, and they form correct beliefs about the quality and quantity of content they produce. Users have an intrinsic interest for each platform and there is perfect information.

The lead application of this paper is closely related to the literature on competition in the media industry. As Hamilton (2006) notes, " "More news is better news" appears to be an axiom favored in discussions about the news marketplace". However, Cage (2017) observes media is characterized by high fixed costs, and finds that competition can decrease the quality of news available to readers. Similarly, we find that the access to more diverse content can lead to a decrease in quality. Importantly, our mechanism does not require entry of new competitors. Inter-newspaper sponsoring exhibits some similarity with news aggregators, in that it helps provide more diversity to users. However, contrary to aggregators, the sponsored content is embedded in the platforms' articles. The latter have a veto right regarding what they display on their pages. Some of the literature (Dellarocas et al. (2013); George and Hogendorn (2012); Jeon and Nasr (2016); and Calzada and Ordóñez (2012)) addresses the tradeoff between the substitution and market expansion effect of aggregators. Several empirical studies show that aggregators do increase traffic to news outlets (Chiou and Tucker (2011)), and benefit specialized outlets, in particular (Calzada and Gil (2016)). Our findings provide support for this hypothesis. Ambrus et al. (2016) highlight a pernicious effect of multi-homing: competing outlets become less wary of increases in advertising levels when users multi-home since marginal consumers are less valuable. The present paper adds to the suspicion against aggregators, by highlighting a different issue caused by business sharing: in the presence of sponsored links, anchored users become less precious relative to roamers.

A key addition to the previous literature on hyperlinking is that any linking is agreed upon by both the sender and receiver of the link. Further, interplatform references need not come for free. A go-between may charge a fee to sponsors, part of which is returned to the publisher who displays the sponsored link. We will observe that these fees have important implications for quality and surplus in equilibrium.

3 Media markets: descriptive evidence of interplatform referencing

Sponsored content started blossoming more than a decade ago in the US.[6] It has now become a standard practice on the World Wide Web. The go-betweens who distribute them have been thriving over the past few years, driving large amounts of revenues. In 2014, the two leading go-betweens, Taboola and Outbrain, reached approximately 500 million unique web users each month.[7] Only four years later, both of these companies claimed they reached twice as many users, and Taboola boasted the third-largest worldwide desktop reach, just ahead of Facebook.[8] For their tenth anniversary in 2018, these companies projected $1 bn of revenue each, which is five times more than in 2014.

In this section we show that high-quality news outlets routinely sponsor their own content within the pages of their competitors, through the medium of go-betweens. We empirically describe the main characteristics of sponsored articles.

We ran a web crawler every night over the period from November 2016 to February 2017. It randomly collected about 85,000 articles from 44 major French information outlets. In total, we observed 650,000 sponsored links (i.e. approximately eight per article on average). This external content is proposed by a go-between, named a "content discovery platform" in the media sector.[9] Out of the 32,000 unique articles from the generalist press, almost 40% included references to competing generalist newspapers. Table 3.1 shows that online newspapers are themselves among the major announcers of their own sector. Strikingly, generalist newspaper Le Monde tops the list of major announcers in other generalist newspapers, with almost 4% of sponsored links referring to its pages.

[6] See New-York times article "Platforms to Use Links to Rivals on Web Sites" http://www.nytimes.com/2006/07/31/technology/31ecom.html

[7] Popular go-betweens, sometimes named "content discovery platforms", include Outbrain, Taboola, Ligatus, Content.ad, Nativo, Revcontent and Adblade. We provide more information about these platforms in Appendix A.2.

[8] See https://www.businesswire.com/news/home/20180307005358/en/comScore-Report-Shows-Taboola-Reaches-World

[9] Content discovery platforms target advertising to specific audiences, with information on individual behavior collected through cookies. We intentionally changed the identification parameters of our crawler for each request. This means that no tracking and targeting can occur. We therefore appeared as a new user throughout the whole period of data collection.

Sponsor	Type of sponsor	Content sponsored (#)
Le Monde	**General press**	12,507
Pause People	Entertainment	8,405
Price Minister	Advertisement	8,339
Actu-orange	**General press**	7,336
Babbel	Advertisement	7,200
Femme Actuelle	Entertainment	7,051
Forsis	Advertisement	6,929
Vie Pratique	Entertainment	5,584
Elle	Entertainment	5,201
Le Figaro	**General press**	3,615
Other		253,460
Total		325,627

Table 3.1: Number of links displayed by content discovery platforms on 25 major French generalist newspapers, ordered by sponsor (source of the link). Articles sampled randomly from November 2016 through February 2017. The table excludes self-promotion.

Most newspapers display some recommendations to external, sponsored content. Figure 3.2 lines up our 44 news outlets around a circle. The arrows show the references made between them through a content discovery platform, on the 3rd of December 2016. The arrows start from the sponsor and point to where the sponsored link has been published. The arrow width is proportional to the number of observed sponsored links.[10] The figure shows that most French online newspapers refer to, or are referred by competitors, or both, through sponsored links.

[10] Yellow labels mean that our robot did not succeed in crawling the website of the newspaper on that day. In that case, it appears as a sponsor only, whereas it may also be a publisher.

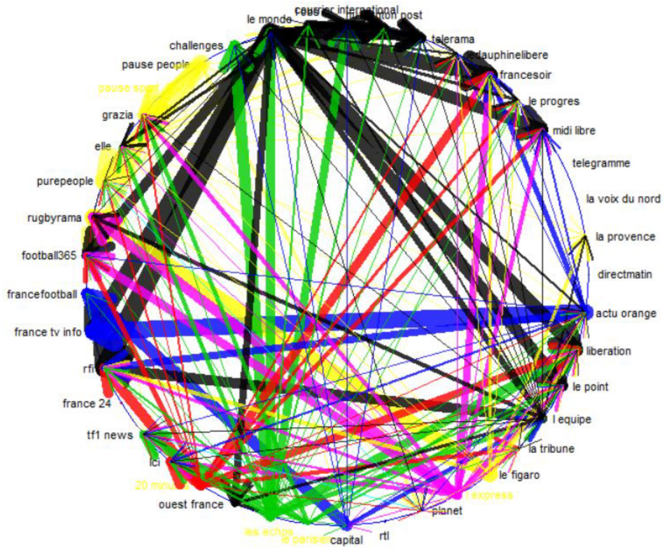


Figure 3.2: Referencing between 44 major French online news outlets, on the 3rd of December 2016.

The nature of our dataset allows for us to provide evidence for a systematic bias towards sponsoring articles on unrelated topics, rather than articles closely related to the publisher's content. Indeed, we collect not only the name of publishers and sponsors, but also the date of publication and title. Most importantly, we collect the actual content of each article. This allows us to estimate how close an article is to the sponsored content – and to all potential candidate articles that may have been sponsored. Using a machine learning algorithm (Latent Dirichlet Association with Gibbs Sampling) which foundations where laid by Blei et al. (2003), we are able to systematically estimate the semantic distance between articles and sponsored content. We use a mixed membership model, which means that articles may be assigned to more than one topic: a set of topics is defined endogenously and the probability that any article belongs to any of these topics is calculated. We compute the semantic distance between two articles i and j as follows:

$$D_{i,j} = \frac{1}{\sqrt{2}}\sqrt{\sum_{t\in T}(\sqrt{p_{i,t}} - \sqrt{p_{j,t}})^2} \tag{3.1}$$

This is the Hellinger distance, later simply referred to as the "distance".[11] T is the set

[11]Other distance measures popular among data scientists include the Kullback-Leibler or Bhattacharyya distances. We also performed the analysis with these alternative measures and found that all of them provided the same qualitative results. For this exercise, our preference goes to the Hellinger

of topics defined by the algorithm and t is any individual topic. $p_{i,t}$ is the probability that article i belongs to topic t. Two perfectly similar articles would therefore have a distance of 0, whereas two articles that unambiguously pertain to two different topics would have a distance of 1. Figure 3.3 shows the average semantic distance between any given pair of articles available in our corpus, which consists of 32,000 articles issued by the 25 generalist newspapers of our sample. The figure shows that actual pairs of published article and sponsored article (lines) are usually more distant semantically than any potential pair in the corpus of all existing articles (bars). This suggests that the algorithms of the go-betweens do not draw randomly the articles to sponsor, but favor articles that are semantically distant from the original article.

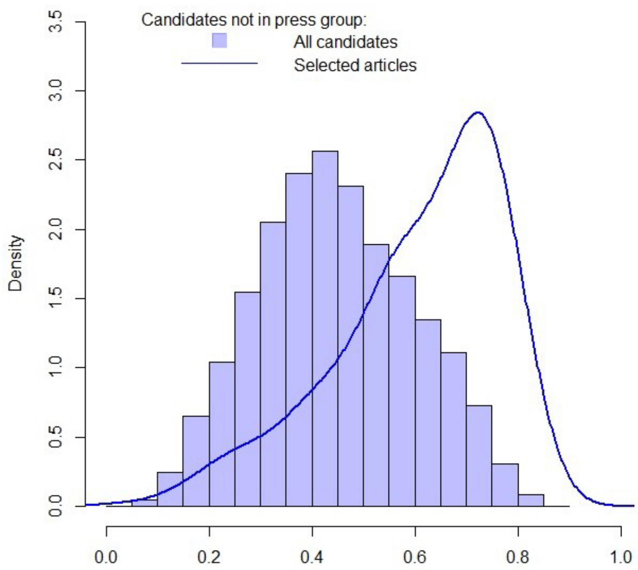


Figure 3.3: Distribution of the semantic distance between any two published articles (bars) and observed pairs of [initial article]-[sponsored article] (lines).

We now produce empirical evidence that sponsored articles are indeed preferably distant from the original article that displays the sponsored link. We also show that these sponsored articles are usually recent. This finding pleads in favor of the relevance of the articles, rather than a "clickbaiting" practice that lures users into viewing low-quality content. To that aim, we closely follow the methodology of Fafchamps and Gubert (2007), who in a different context but formally equivalent setting estimate the impact of distance between agents on their decision to build a link. We estimate a dyadic

distance, because it is a metric. In particular, it is symmetric and satisfies the triangle inequality.

regression of the form

$$
\begin{aligned}
Y_{ij} =& \alpha_0 + \alpha_1 Distance_{ij} * same\_group_{IJ} + \alpha_2 Elapsed\_time_{ij} * Same\_group_{IJ} \\
&+ \alpha_3 Length_{jJ} * Same\_group_{IJ} + \alpha_4 Catchy_j * Same\_group_{IJ} \\
&+ Same\_group_{IJ} + \delta_I + \eta_J + u_{ij} \,, \qquad (3.2)
\end{aligned}
$$

where Y_{ij} is 1 if article i displays a link to article j (i.e. article j is sponsored in article i) and 0 otherwise. $Distance_{ij}$ is the semantic distance between articles i and j as defined in equation (3.1). $Same\_group_{IJ}$ takes the value 1 if the newspaper I of article i belongs to the same press group as the newspaper J that produced article j and 0 otherwise. $Elapsed\_time_{ij}$ is the time difference between the publication dates of articles i and j. $Length_{jJ}$ is how long (in number of words) article j is, relative to the average for the corpus of all articles issued by newspaper J. An article is defined as "catchy" if the title includes a question or exclamation mark, or addresses readers directly ("you"...). δ_I and η_J are publishers and sponsors fixed effects. u_{ij} is an error term. For any given article i the high number of potential sponsored articles j renders the semantic analysis computationally infeasible. We therefore reduce the sample in two manners. First, we focus on generalist press only (25 newspapers) and consider only links to sponsored articles that also appear in our base sample of published article. This methods reduces the sample to 6,300 observation pairs. Second, for each pair ij we observe, we randomly select 99 articles that could have been sponsored in i. These 99 articles are randomly drawn among all articles previously published by all other generalist newspapers other than I. This means that our final sample includes 630,000 observations. Here, we exploit a classic result by McFadden (1978), who showed that random subsampling of a choice set does not render estimates inconsistent. We present the results of our logistic regressions in Table 3.2. The first column reports the result without *Same_group* interactions. The second and third columns are model (3.2) with and without newspaper fixed effects, respectively.

These regressions show that sponsored articles often treat topics that are different from the article from which the reader started. Recent articles are more likely to be selected. Recent articles are more likely to be selected. Also, contrary to the clickbait practice, having a catchy title decreases chances to be sponsored. These facts are indicative evidence that content is indeed of some relevance to readers, in the sense they provide recent information about topics they may not have already read about. The second column shows that newspapers preferably select articles issued by their own press group, especially if these are "catchy". They allow for more proximity of the sponsored

	Dependent variable:		
	Sponsored article		
	(1)	(2)	(3)
Distance	5.01*** (0.64)	6.80*** (0.74)	8.45*** (0.66)
Elapsed_time	−0.14*** (0.02)	−0.13*** (0.02)	−0.12*** (0.02)
Length	0.002 (0.02)	0.03 (0.03)	−0.002 (0.03)
Catchy	−0.19 (0.17)	−0.57** (0.23)	−0.69*** (0.16)
Same_group	0.98** (0.46)	3.61*** (0.64)	4.32*** (0.61)
Distance:Same_group		−4.47*** (1.23)	−5.75*** (0.97)
Same_group:Elapsed_time		−0.04 (0.04)	−0.04 (0.04)
Same_group:Length		−0.06 (0.03)	−0.03 (0.04)
Same_group:Catchy		0.85*** (0.30)	0.98*** (0.23)
Constant	−5.64*** (0.37)	−6.75*** (0.47)	−7.45*** (0.57)
Publisher and Sponsor FE	no	no	yes
Observations	629,996	629,996	629,996
Log Likelihood	−27,614.74	−27,186.40	−23,454.80
Akaike Inf. Crit.	55,241.47	54,392.80	47,013.60

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors in parentheses, clustered at the publisher and promoter level.

Table 3.2: Estimation of model (3.2) with logit estimator.

content to the original article if the sponsored content was issued by a newspaper that belongs to the same press group. This result may be rationalized by a smaller revenue loss incurred when readers leave the initial newspaper but stay within the same press group.

A key assumption of our model, in line with the stated mission of content discovery platforms, is that references direct towards new, relevant content rather than duplicates that could steal traffic from the publisher of the link. References therefore provide users with more diverse content and increase overall traffic. This empirical study shows this assumption is likely to be verified in practice.

Taking stock of this observation, we now question why the promotion of competitors may happen (Section 4) and assess its impact on competition (Section 5). Finally, we question whether regulators should like the “content you may like” (Section 6).

4 Base model and benchmark

4.1 Base model

We examine the case of two differentiated platforms, 1 and 2. They produce content with the following process. Assume that there are in total N items that users may be interested in (in the media application, there would be N events happening on a given day). Platforms are endowed with symmetric technologies that enable them to find each of these items with an independent probability $\tau > 0$. Not all of these items may be interesting to all users. We assume a given user is interested in any given article with probability ρ. Hence, in expectation, users are interested in viewing $\rho\tau N$ pages on each platform. $2\tau(1-\tau)$ is the probability that an item is found by exactly one platform. We denote $K \equiv \rho\tau N$ and $k \equiv \rho\tau(1-\tau)N$. K represents the expected number of items of interest on any of the platforms. k is the expected number of items of interest in any of the platforms, that were not found by the other platform. As illustrated in Figure 3.4, this means that platforms found in total $K+k$ items relevant to any given user, of which each platform found only K, of which $K-k$ are common to both platforms and k are original to each platform. In the body of the paper, K and k are exogenous and will be used, when references are present, as a measure of the extent of roaming (measured by k) relative to anchored viewership (measured by K).[12]

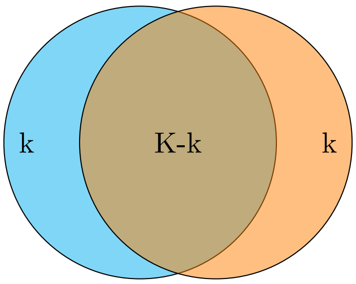


Figure 3.4: Content overlap between platforms 1 (left, blue circle) and 2 (right, orange circle).

Platforms compete for users of type R and type A, each constituting a side of the market. When platforms are media websites, A-users are advertisers. R-users are readers surfing the web in search of information. We focus on free-access websites, meaning that platforms compete in quality to attract R-users and in turn, the more lucrative A-users.

[12]Online Appendix OA.4 endogenizes the production of articles instead of quality and shows that our qualitative results are maintained.

Throughout the paper, we make a clear distinction between "multi-homing" and "roaming". We say an R-user multi-homes if she actively visits the homepage of more than one platform, without using references. For each visit, she incurs a visit cost s. It represents the opportunity cost of time to visit a website and identify which of its items are of interest. When the R-user simply clicks on references embedded in platforms' pages, we say she "roams" to external content. We assume roaming is costless to users, since go-betweens steer them directly to the items they may be interested in. The "anchor" platform of an R-user is the website she visits first.[13]

The three paragraphs below explain in more detail the role of each of the three categories of agents: type-R and type-A users and platforms.

R-users: R-users are individuals searching for information. They are uniformly distributed on a unit Hotelling line with preference parameter t_r. x indexes the distance to platform 1. Platforms 1 and 2 are located at each extremity of the line, namely $x_1 = 0$ and $x_2 = 1$. In the media application of our model, the interpretation is that R-users are looking for interesting news stories to read, preferably from the "closest" newspaper – i.e., the one that fits their preferences or political inclination best. In addition to these horizontal preferences, R-users are also interested in quality, which is a vertical differentiation parameter. Quality is produced, at a cost, by platforms. It represents the editorial quality of content, a nice interface or additional services.

Take an R-user located at distance x of platform i, anchored with platform i. Her utility is generated as follows. First, she derives an intrinsic benefit of subscription $\bar{u}_r$. In the newspaper application it represents the intrinsic satisfaction of being informed of the most important daily news. She also incurs a visit cost s, which we assume is lower than $\bar{u}_r$. Once in platform i, she enjoys the quality q_i of platform i, for each of the items she views. A preference cost $t_r \mid x - x_i \mid$ is also incurred for each of these items. In media, it represents the disutility from imperfect preference matching between an article's political inclination and R-users tastes. We denote by $v^{i,i}$ the number of items the R-user expects to view in her anchor platform i.

Then, she may decide to also visit her platform of second choice j, either by actively visiting j, or simply by following sponsored links if they are present. In that case, she may view $v^{i,j}$ items produced by j. It corresponds to the number of items produced by j that an R-user anchored with i may be interested in viewing after having viewed the

[13] As in Dellarocas et al. (2013), we motivate the notion of an anchor website by the fact web users tend to use only a very limited number of information sources (Mitchell and Skrzypacz (2006); Purcell et al. (2010); Ofcom (2014); Gentzkow and Shapiro (2011)).

items of i. These items have the attributes (quality and horizontal characteristics) of platform j. Adding these terms together, the utility of an R-user anchored with platform i is :

$$U_r^i(x,k) = \bar{u}_r - (1+MH)s + (q_i - t_r \mid x - x_i \mid)v^{i,i} + (q_j - t_r \mid x - x_j \mid)\, v^{i,j}\,, \tag{3.3}$$

A single-homing R-user pays the visit cost only once ($MH = 0$). It is paid twice if she visits both platforms directly ($MH = 1$). The third term corresponds to surplus generated by visiting platform i. The fourth term is the surplus extracted while viewing the content of the platform of second choice j. Absent references, single homing users don't view any of the content of their platform of second choice ($v^{i,j} = 0$).

A-users: There is a unit mass of A-users. These are firms interested primarily in interacting with R-users. They have no preference for a specific platform but want to interact with as many R-users as possible, as many times as possible. The utility of an A-user joining platform i is:

$$U_a^i(k) = (\alpha_a - \gamma_i)V^i \tag{3.4}$$

α_a is the intrinsic benefit that an A-user enjoys from interacting with an R-user. In the media sector, it corresponds to persuasive advertisement where the value of an impression is independent of how many times a R-user may have seen the advertisement. γ_i is a cost-per-click, or interaction fee paid by the A-user to the platform for each interaction with an R-user. The A-user utility is therefore proportional to V^i, the total number of clicks (items viewed) on platform i. V^i, which we calculate in the next section, is the sum of all views to platform i, whether the R-users that generate them are anchored or not.

Platforms: Platforms invest in quality q_i so as to attract R-users and in turn the A-users. We denote by n_r^i the number of R-users anchored with platform i. Platforms aim at maximizing profits:

$$\Pi_i(\gamma_i, q_i, \gamma_j, q_j) = \gamma_i V^i + \mathbb{1}_{gb}\left(f n_r^i v^{i,j} - F n_r^j v^{j,i}\right) - c_i q_i^2 \tag{3.5}$$

The first term corresponds to revenues derived from A-users, who are willing to pay in order to access the R-users of platform i. $\mathbb{1}_{gb}$ takes value 1 if there is a go-between. In that case, users have no reason to multi-home: they use the links of the go-between to roam to their platform of second choice, thereby saving the visit cost s. We can decompose the payments of go-betweens into two components: the first component corresponds to the publisher fee f paid by the go-between to platform i if its anchored R-users click on a link published by i, directing to platform j. The go-between pays this fee $v^{i,j}$ times for each R-user anchored in i. The second component represents the sponsoring fee F that platform i pays to the go-between in order to have R-users anchored in j roam to its own platform i. This fee is paid $v^{j,i}$ times per roamer. F therefore essentially constitutes a fine a platform has to pay in order to receive views from users who decided not to elect him as an anchor platform in the first place. The last term in (3.5) is the cost of quality provision. c_i is the rate at which the provision of quality becomes marginally more expensive. For simplicity we assume in the body of the paper costs are symmetric $c_1 = c_2 = c$. We relax this assumption in Appendix B.2.

Timing: The timing of the general game has three stages:

1. A monopolistic go-between fixes reference fees f and F, and chooses the items to be sponsored. Platforms accept or reject to publish and/or sponsor.
2. Platforms simultaneously choose quality q_i and price γ_i.
3. Users observe q_i, γ_i and choose their "anchor" platform. R-users may multi-home to the platform of second choice, or simply "roam" at no cost if sponsored links are present.

In stage 1 we assume, to fix ideas, that the go-between is an uncontested monopoly. Other market structures are studied in Section 6. We look for subgame-perfect Nash equilibria.

4.2 Benchmark with no interplatform references

We first start with the benchmark case in which there is no go-between: $\mathbb{1}_{gb} = 0$. There is therefore no stage 1 and R-users cannot roam through references. However they may multi-home, i.e., visit each platform by themselves. Visiting either or both platforms is a two-stage decision and we decompose utility (3.3) into two terms : $U_r^i(x,k) = u_r^{i,i}(x,k) + u_r^{i,j}(x,k)$. The first term is the utility derived from the first visit to a platform i:

$$u_r^{i,i}(x,k) = \bar{u}_r - s + (q_i - t_r \mid x - x_i \mid)v^{i,i}\,, \tag{3.6}$$

The R-user extracts the intrinsic satisfaction of information $\bar{u}_r$, and incurs the cost of a visit $s < \bar{u}_r$.[14] The second term is the utility derived from a second visit. It does not generate the intrinsic satisfaction $\bar{u}_r$:

$$u_r^{i,j}(x,k) = -s + (q_j - t_r \mid x - x_j \mid)\, v^{i,j}\,, \tag{3.7}$$

R-users visit both platforms if the expected surplus derived from the extra content of the platform of second choice weakly exceeds the visit cost s (i.e. equation (3.7) is nonnegative). Once visit costs s are paid and sunk, we assume that users always derive nonnegative surplus from viewing any content, even from the platform least close to their preferences. We will see further that this requires that the cost of provision of quality be not too high (assumption A0):

A0: $c \leq \frac{\alpha_a(K-k)}{4t_r^2}$

Under assumption A0 an R-user views all items of interest in the anchor platform i: $v^{i,i} = K$. If she multi-homes, she views all of the remaining items of interest in the target of roaming j: $v^{i,j} = k$. If the R-user single-homes $v^{i,j} = 0$. We denote by $n_r^{i,MH}$ the number of multi-homers anchored with i, i.e., R-users who start with i, and then also visit the platform of second choice j. The total number of clicks on platform i is:

$$\begin{aligned} V^i =& n_r^i v^{i,i} + n_r^{j,MH} v^{j,i} \\ =& n_r^i K + n_r^{j,MH} k \end{aligned} \tag{3.8}$$

Define $\underline{\underline{s}} = k\left(\frac{\alpha_a}{4ct_r}(K-k) - t_r\right)$, $\underline{s} = k\left(\frac{\alpha_a}{4ct_r}(K+k) - t_r\right)$, $\overline{s} = k\left(\frac{\alpha_a}{4ct_r}\left(K + \frac{k}{4}\right) - \frac{t_r}{2}\right)$, $\overline{\overline{s}} = k\left(\frac{\alpha_a}{4ct_r}\left(K + \frac{3k}{4}\right) - \frac{t_r}{2}\right)$. We assume k is sufficiently small such that these thresholds are all distinct from each other and $\underline{\underline{s}} < \underline{s} < \overline{s} < \overline{\overline{s}}$.

Proposition 3.1 lists the Nash equilibria of the game. It describes the equilibrium quality and multi-homing adoption as a function of visit cost s.

Proposition 3.1 (no go-between)**.** *Assume A0 and that there is no go-between. Define $q^* = \frac{\alpha_a K}{4ct_r}$, s the exogenous cost of a visit to a platform and $m(s) = 2\frac{q^*\left(1+\frac{k}{K}\right)-\frac{s}{k}}{t_r} - 1$:*

- *If $s \leq \underline{\underline{s}}$, all R-users multi-home. The quality is $q = q^*\left(1 - \frac{k}{K}\right)$.*
- *If $\underline{\underline{s}} < s \leq \underline{s}$, all R-users multi-home. The quality is $q = t_r + \frac{s}{k}$.*

[14] An alternative but equivalent specification would be to set both the cost of the first visit and the intrinsic satisfaction to 0.

- *If $\underline{s} < s < \overline{s}$, there are $m(s)$ multi-homers. The quality is $q = q^*(1 + \frac{k}{K})$.*
- *If $\overline{s} \leq s \leq \overline{\overline{s}}$, three equilibria coexist:*
  - *There are $m(s)$ multi-homers. The quality is $q = q^*(1 + \frac{k}{K})$.*
  - *There is no multi-homing. The quality is $q = q^*$.*
  - *There is an equilibrium in mixed strategies*
- *If $s > \overline{\overline{s}}$, there is no multi-homing. The quality is $q = q^*$. (**Benchmark case**)*

For all s, $\gamma_i = \alpha_a$.

Proof. Since A-users multi-home, our situation corresponds to a typical competitive bottleneck (see Armstrong and Wright (2007)). Consequently for all s, all A-users' surplus is fully extracted in equilibrium ($\gamma_i = \alpha_a$). For equilibrium quality and multi-homing decisions, see Appendix B.1. □

Figure 3.5 illustrates the findings of Proposition 3.1.

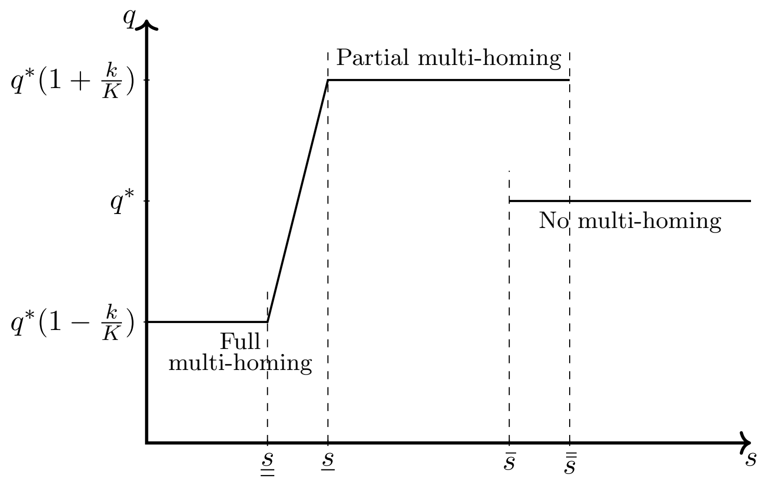


Figure 3.5: Equilibrium quality in pure strategies without a go-between, as a function of the cost of a visit s

If visit costs are small ($s < \underline{\underline{s}}$) and there is no go-between, all R-users multi-home. In that case it is immediate that introducing a go-between is always (weakly) beneficial to all agents, and to social surplus: its only effect is to allow users to roam to external content directly, without them paying the costs s of a second visit. In the remainder of the paper, we focus on the more interesting benchmark case when at least some R-users single-home.

Proposition 3.1 shows that the possibility of partial roaming (i.e. when $s \in [\underline{s} : \bar{\bar{s}}]$) increases equilibrium quality compared to a situation in which all users single-home ($s > \bar{\bar{s}}$). This result is in sharp contrast with most of the literature, in which prices (which could be interpreted here as negative quality) increase on the side that multi-homes. First, we note that the decision to anchor in i or j is still exclusive of anchoring in the other platform, and therefore platforms still compete head-to-head for anchored R-users. If platforms competed only for anchored users, multi-homing would indeed soften competition since marginal non-anchored users are multi-homers and yield a positive value to the platform of second choice. However, when multi-homing is only partial, platforms also have an incentive to increase quality and induce more non-anchored users to roam to their content. In our model, the second effect prevails. This result is reminiscent of Belleflamme and Peitz (2018) where an increase in the elasticity of demand can result in the multi-homing side being treated favorably.

Selecting partial multi-homing as a benchmark ($s \in [\underline{s} : \bar{\bar{s}}]$) would strengthen the magnitude of our results but would also substantially complicate the exposition. Hence, in the body of the paper, we focus on the simpler case in which a second visit would decrease all R-users' surplus ($\bar{u}_r > s > \bar{\bar{s}}$). This means our benchmark corresponds to type-R full single-homing: like in Calzada and Tselekounis (2018) users don't do a second visit because of high intrinsic costs of a visit s and a large content overlap $(K-k)$ between the two platforms. The benchmark equilibrium quality is $q^* = \frac{\alpha_a K}{4ct_r}$.

Appendix C studies the other possible benchmarks and shows all our results are qualitatively maintained even if the benchmark is one of partial multi-homing.

5 The effect of interplatform references on competition

We now introduce the go-between, which allows interplatform referencing. It relates a publisher platform (say platform i) with a sponsoring platform (platform j). Due to its technology, the go-between algorithmically identifies the k items of interest in the platform of second choice j. It displays hyperlinks within the pages of platform i, thereby allowing for the R-users to roam directly to the content of j in a costless manner. We will show further that R-users therefore have no reason to multi-home (i.e. actively visit the home page of the other platform), when references are present in their anchor platform. Instead, they simply click on sponsored links. References can, and are in general reciprocal: in equilibrium, both platform 1 and 2 are sponsors and publishers.

The go-between charges its intermediation service on a per-click basis: if an R-user anchored in i clicks on some content sponsored by j, the sponsor platform j pays a fee F to the go-between, and the go-between pays back f to the anchor website i. $F - f$ is the remuneration of the go-between. While our model does not require a more precise modeling of go-betweens the interested reader will find a more detailed description of go-betweens in the media sector and their business model in Appendix A.2.

We solve the game by backward induction.

5.1 Stage 3: User choices

Utility functions of R- and A-users are the same as in (3.3) and (3.4). Although references may be unidirectional, we observe in the next section that the go-between always finds it optimal to offer reciprocal deals, with all k items of interest of each platform being sponsored. Hence we focus on the symmetric case when both platforms sponsor and publish the same number of links k. Figure 3.6 illustrates graphically type-R users' problem and the role of the go-between.

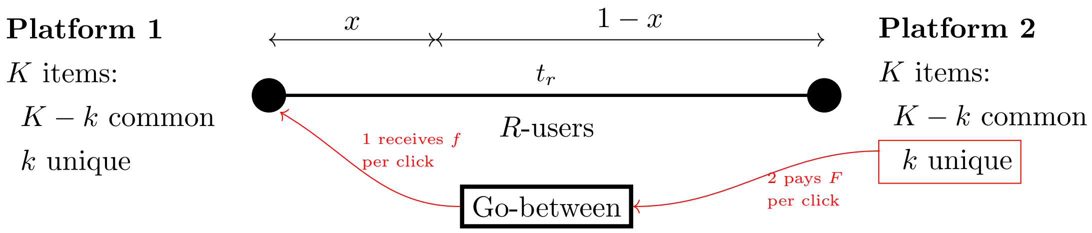


Figure 3.6: A go-between allows R-users anchored in platform 1 to access the unique content of platform 2. For clarity, the reciprocal referencing from platform 1 to 2 is not shown in this graph.

Again, we take c sufficiently small so that, with zero-visit costs, all R-users view all content they have access to. We make an assumption similar to A0:

A1: $c \leq \frac{\alpha_a(K-k)+k(f+F)}{4t_r^2}$

A1 ensures that the costs of provision of quality is sufficiently low so that equilibrium quality induces all R-users to roam whenever there are references. Under assumption A1 all users view the K items of their anchor platform and view the k sponsored links ($v^{i,i} = K$ and $v^{i,j} = k$). With the utility functions defined in (3.3) and (3.4), we can solve stage 3 of the game. The number of users anchored in i is :

$$n_r^i = \frac{1}{2} + \frac{q_i - q_j}{2t_r} \tag{3.9}$$

All A-users join platform i if and only if $\gamma_i \leq \alpha_a$.

5.2 Stage 2: Decisions of platforms

We now turn to stage 2. The profit function is given by equation (3.5) with $\mathbb{1}_{gb} = 1$. Under assumption A1, the platforms' profit function reduces to:

$$\Pi_i(q_i, q_j) = \alpha_a(n_r^i K + n_r^j k) + \left(f n_r^i - F n_r^j\right) k - c q_i^2 \tag{3.10}$$

Proposition 3.2 describes the unique equilibrium in stage 2 of the game, when platforms have accepted to publish and sponsor content.

Proposition 3.2 (Equilibrium quality)**.** *Assume A1 holds, $s > 0$, and there is interplatform referencing. There exists a unique Nash equilibrium of stage 2, which is symmetric. All R-users single-home and use references to roam between platforms. Equilibrium quality and prices are :*

$$q_i(k) = q^* - k\frac{\alpha_a - (f + F)}{4ct_r} \tag{3.11}$$

$$\gamma_i(k) = \alpha_a\,, \tag{3.12}$$

where $q^* = \frac{\alpha_a K}{4ct_r}$ is the equilibrium quality when there are no interplatform references $(k = 0)$.

Proof. Since A-users are undifferentiated and may multi-home, our situation corresponds to a typical competitive bottleneck. (3.12) is the interaction fee that captures all surplus from these users. Profit maximization of (3.10) with demand function (3.9) yields (3.11). We verify that under assumption A1 , $q_i(k) \geq t_r$, meaning all R-users follow sponsored links to roam to external content. Appendix B.2 provides the detailed proof with general, asymmetric cost functions. □

We observe that if fees f and F are small, references induce a softening of the competition for R-users: quality, which is prized by R-users, decreases with the number of sponsored links k. Indeed, even if an R-user switches anchor platforms, the losing platform can still recover some viewership of that very user through sponsored links.

This decreases platforms' incentives to provide quality and attract R-users in the first place. This effect is mitigated by the sponsoring fee F that platforms must pay to the go-between in order to attract these users. Indeed, attracting roamers becomes more costly as F increases, which induces platforms to produce higher quality so as to encourage R-users to anchor, instead of roaming to their content. Additionally, interplatform references constitute an incremental source of revenues for publishers. Due to outgoing links, the value of any given anchored R-user increases from $\alpha_a K$ when there are no interplatform references to $\alpha_a K + fk$ when there are. Anchored users mechanically become more valuable to platforms who in turn increase their efforts to attract them.

Corollary 3.1 compares the equilibrium outcome when there is a go-between to the benchmark case when there is not.

Corollary 3.1. *Assume s is large enough ($s > \bar{\bar{s}}$). If reference fees are low, the introduction of interplatform references decreases the equilibrium quality. High fees induce an increase in equilibrium quality.*

Proof. The proof derives from a comparison of the equilibrium quality with a go-between (3.11), with the equilibrium quality of Proposition 3.1, when $s > \bar{\bar{s}}$ □

5.3 Stage 1: Reference fees

In stage 2, platforms take the presence of references and their fees as given. However, not all reference fees would be accepted by platforms in stage 1. Denote by $\Pi_i(k_j, f, F)$ and $\Pi_g(k_j, f, F)$ the equilibrium profits of the platforms and the go-between, respectively, when j sponsors $k_j \leq k$ of its k unique items within the pages of i, and reference fees are f and F. We denote with a star superscript the equilibrium profits without references.

Definition 1. *Fix $k_j > 0$. A set of fees (f, F) is feasible if it satisfies the participation constraints of both platforms and the go-betweens. We denote the set of feasible fees by*

$$\mathscr{F} \equiv \{(f, F) \in \mathbb{R}^2 / \forall i \in 1, 2, \Pi_i(k_j, f, F) \geq \Pi_i^*, \Pi_g(k_j, f, F) \geq 0\}$$

This definition simply states that for sponsored links to be displayed, all agents involved in the decision to display the external links must derive a nonnegative profit from these links. Note that this definition does not require links to be reciprocal: platforms can unilaterally decide to only sponsor or publish external content.

Platforms may anticipate that providing their own content to a rival increases fringe users' incentives to anchor in the rival website (see utility function 3.3): indeed, a sponsor is less willing to pay for roamers if it induces a loss in anchored users. Conversely, publishers may accept lower payments if external content helps them to attract R-users. Lemma 1 shows that a go-between can always find a fee structure that generates nonnegative profits and induces platforms to unilaterally accept either sponsoring and publishing external content.

Lemma 1 (Feasible set with full information)**.** *Assume platforms have full information and are perfectly rational. The feasible set $\mathscr{F}$ is nonempty and bounded.*

Proof. See Appendix B.3. ☐

While Lemma 1 suffices for our purpose, the feasible set does not have a simple, explicit formulation. Slightly relaxing the rationality or information available to platforms results in $\mathscr{F}$ having a simple characterization. Lemma 2 provides an explicit definition of the feasible set when platforms do not observe the fees faced by their competitor.

Lemma 2 (Feasible set with partial information)**.** *Assume platforms have a prior over the fees faced by the other platform. There exist boundaries $(\underline{f}, \bar{F}) \in \mathbb{R}^2$ such that*

$$\mathscr{F} = \{(f, F) \in \mathbb{R}^2 / f \leq F, f \geq \underline{f}, F \leq \bar{F}\}$$

Proof. See Appendix B.3. ☐

Hence, the feasibility set when platforms have limited information is a triangle. Bounded rationality of the platforms also results in the feasibility being a triangle. The simple case of Lemma 3 conveys the intuition for the nonemptiness of $\mathscr{F}$, when platforms are naive, in the sense they focus on short term gains and neglect the effect of references on user participation. It yields simple expressions of the boundaries $\underline{f}$ and $\bar{F}$ of the feasible set.

Lemma 3 (Feasible set with naive platforms)**.** *Assume platforms are naive: they neglect the effect of references on user participation and focus on referencing revenues only. The set of feasible fees is*

$$\mathscr{F} = \{(f, F) \in \mathbb{R}^2 / f \leq F, f \geq \underline{f} = 0, F \leq \bar{F} = \alpha_a\}$$

Proof. The mechanism that underlies Lemma 3 is simple: a sponsor's individual rationality imposes that F does not exceed $\bar{F} = \alpha_a$. Above $\bar{F}$, no platform would be willing to sponsor any content since sponsoring costs would exceed the advertising profits a platform expects to derive from a roamer. Individual rationality of publishers imposes that f be nonnegative; otherwise, publishing the content of competitors would result in a direct loss for the publisher. Finally, the participation constraint of the go-between imposes that the cost-per-click margin is nonnegative, i.e., $f \leq F$. $\square$

The go-between seeks to maximize the margin $F - f$, under the constraint that platforms both accept to publish external content and sponsor theirs. Equipped with the characterization of the feasible set, we can derive the fees that a monopolistic go-between sets in stage 1.

Proposition 3.3 (Monopolistic go-between)**.** *A monopolistic go-between with full bargaining power maximizes the margin between fees, within the feasible set. If platforms have bounded rationality or form priors about the fees faced by their competitor, this translates into $f = \underline{f}$ and $F = \bar{F}$.*

Proof. The go-between profit is: $\Pi_g(f, F, k_j) = (F - f)k_j \mathbb{1}_{(f,F)\in\mathscr{F}}$. When the feasible set is defined as in Lemma 2 (platforms have limited information) or Lemma 3 (bounded rationality), $f = \underline{f}$ and $F = \bar{F}$ ensure that the margin is maximized, under the constraint that fees are in the feasible set $\mathscr{F}$. $\square$

We note that profits are infinitely differentiable in k. For k small enough, all incremental profits are linear in k. This means that if fees are feasible, all unique articles are sponsored: $k_j = k$. We exhibited the conditions for platform j to sponsor its content within the pages of platform i. Given the symmetry of the model, we finally note that the go-between rationally sells reciprocal services: $k_j = k_i = k$.

6 Welfare analysis: should regulators like the "content you may like"?

Section 6.1 analyzes the impact of references on user welfare, the profits of platforms, and the social surplus for a generic set of fees (f, F). We characterize how reference fees affect these values and conclude that a social planner would likely want reference fees to be as high as possible. Section 6.2 shows that this conflicts with the interests of the go-between and those of the platforms. It shows that competition among several go-betweens results in the adoption of the fees that maximize quality and user surplus. Under mild conditions it coincides with the welfare-maximizing fees. Section 6.3 derives policy implications.

6.1 Surplus analysis

We successively analyze the impact of references on the surplus of R-users, platforms' profits and social welfare. We assume that s is large enough, so that the benchmark case corresponds to full single homing of R-users in the absence of a go-between.

R-user surplus: On the one hand, the R-user surplus increases as they access more diverse content (R-users view $K+k$ items instead of K in the absence of references). On the other hand, the quality of each item decreases. To identify which of the two effects prevails, we calculate the increment in utility for a R-user located in x and anchored with platform i, which we denote $\Delta U_r^i(x,k) \equiv U_r^i(x,k) - U_r^i(x,0)$:

$$\Delta U_r^i(x,k) = K\overbrace{(q_i(k) - q_i(0))}^{\text{quality effect}} + k\overbrace{(q_i(k) - t_r(1-x))}^{\text{diversification effect}} \tag{3.13}$$

Using $q_i(0) = q^* = \frac{\alpha_a K}{4ct_r}$, and normalizing by the number of references, we derive

$$\frac{1}{k}\Delta U_r^i(x,k) = -\frac{k}{K}q^* + (K+k)\frac{f+F}{4ct_r} - t_r(1-x) \tag{3.14}$$

A first immediate result is that when fees are small, the presence of references results in a decrease in utility for R-users. This result is despite the increase in content diversity. Surprisingly, this is true for all users, including those with weak preferences ($x = \frac{1}{2}$), who are those who enjoy the content of their platform of second choice the most. This finding is due to the fact that the decrease in quality affects not only the k original content but the whole corpus of K items produced by each platform.

Figure 3.7 illustrates the effects of f and F on user surplus. In order to maximize R-user surplus, interplatform fees should be set as high as possible. The following proposition summarizes these findings.

Proposition 3.4 (User surplus)**.** *Assume A1, and that reference fees (f, F) belong to the feasible set $\mathscr{F}$:*

1. *Conditional on the presence of interplatform references, user surplus is maximized when reference fees are at the maximum feasible level.*

2. *With quadratic costs of quality provision, interplatform references increase user surplus if and only if the associated reference fees f and F are sufficiently high.*

Proof. The proofs of result 1 and 2 derive from previous discussions and the analysis of relation (3.14). With quadratic costs, references increase the surplus of all users if and only if $f + F \geq \frac{4ct_r^2 + k\alpha_a}{K+k}$. In fact, a sufficient result 2 to hold is that the cost of quality provision $C(q)$ be such that $C'(0) \geq 0$ and $C'''(q) \leq 0$. A detailed proof is provided in the case of general cost functions in Appendix B.4. $\square$

The intuition for this proposition is that the sponsoring fee F makes the attraction of roamers through sponsored links costly. The publisher fee f renders anchored R-users more profitable. Therefore, both fees restore incentives to invest in quality, which entices users to anchor. Interestingly Proposition 3.4 is true even in the likely case when the marginal cost of distribution of sponsored links is 0.

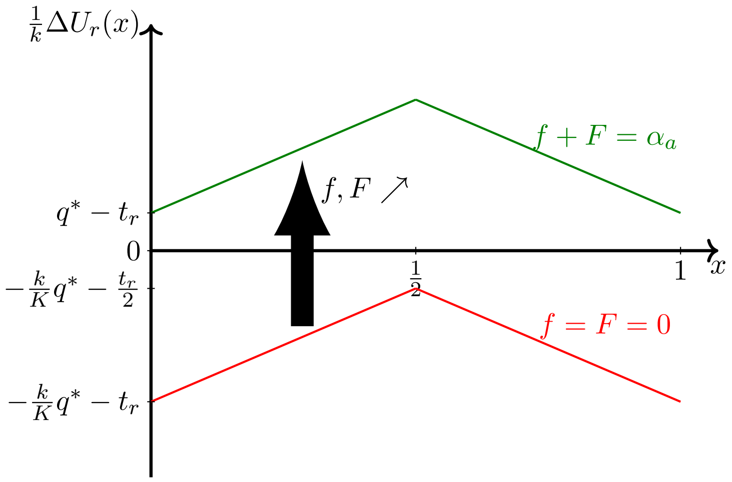


Figure 3.7: Incremental user surplus when there are interplatforms references, as a function of the preferences of users.

Platform profits: The following proposition shows that platforms, contrary to users, benefit from low fees.

Proposition 3.5 (Platforms profits)**.** *Assume A1 and that reference fees (f, F) belong to the feasible set $\mathscr{F}$. Interplatform references increase platform profits if and only if the associated reference fees f and F are sufficiently low. Platform profits are maximized when reference fees are at the minimum feasible level $f = F = \underline{f}$.*

Proof. Profits can be expressed as follows:

$$\Pi_i(k, f, F) = \Pi_i(0) + \frac{k}{2}(\alpha_a + f - F) - c\left(q^2(k) - q^2(0)\right) \tag{3.15}$$

Denote $\Delta\Pi_i(k) \equiv \Pi_i(k) - \Pi(0)$ the increase in equilibrium profits of each symmetric platform when there are references. The incremental profit normalized by the number of references is:

$$\frac{1}{k}\Delta\Pi_i(k, f, F) = \frac{\alpha_a - (F - f)}{2} + c\frac{\alpha_a - (f + F)}{(4ct_r)^2}(\alpha_a(2K - k) + k(f + F)) \tag{3.16}$$

It is easy to show that $F = f = \underline{f}$ is the set of feasible fees that minimizes equilibrium quality and, in turn, maximizes the joint profits of platforms (see Appendix B.5 for a formal proof in the case of general cost functions). □

These fees bear a formal similarity with the termination fees of the literature on telecommunication. However, our results contrast sharply with most models of co-opetition, in which optimal termination fees are low: Laffont, Rey and Tirole (1998), proposition 2 and Armstrong (1998) show that *low* termination fees promote competition and firms want *high* fees. Similarly, Armstrong (1999) shows that pay-TV operators may replicate the collusive outcome by agreeing on high reciprocal access charges. The fundamental reason for the polar difference between the conclusions of this literature and our conclusions, is that reference fees are paid by the platform where users terminate usage and not the platform they started from. In our case, increasing the publisher fee f increases the intrinsic value of anchored users, and increasing the sponsor fee F decreases the value of roamers. Both forces push for more quality competition between platforms.

With these profit functions we can describe another interesting situation. When go-betweens bundle their services, i.e., platforms have to accept to both sponsor and publish, or reject any deal, the feasible set is not bounded by $\underline{f}$:

Example 2 (Bundling of sponsorship and publishing)**.** *Assume A1. If the go-between bundles its publication and sponsoring services, any fees (f, F) such that $f = F \leq \frac{\alpha_a}{2}$ are feasible.*

Proof. The proof is easily derived from the analysis of platforms equilibrium profits (3.16), and the observation that references actually occur if and only if both platforms accept the sponsoring bundle. In that case, it is a dominant strategy to accept the deal as soon as expected future equilibrium profits are greater with than without sponsoring.

If k is small, we can express the maximum sum of fees $\bar{F}$ such that go-betweens make a nonnegative margin $m \equiv F - f$. Any fees such that $f + F < \bar{F} = \alpha_a + \frac{4ct_r^2}{K\alpha_a}(\alpha_a - m)$ belong to the feasible set, as long as they are not as high as to violate assumption A1. □

It appears, however, that in practice go-betweens in the media sector do not impose bundle services. Hence in the remainder of the paper, we assume that the feasible set is defined as in Lemma 1, that allows for references to be unidirectional.

Social surplus : We saw that market participants have diverging interests regarding the setting of reference fees. The go-between is primarily interested in the margin between the two fees (Proposition 3.3). Users want fees to be as high as possible such that platforms compete fiercely for them (Proposition 3.4). Conversely, platforms aim at softening competition and prefer low fees (Proposition 3.5). A social planner biased towards some agents rather than others could favor any convex combination of such fees. We assume here that the social planner is unbiased.

Proposition 3.6 (Social welfare)**.** *Assume A1. For any set of fees (f, F), there exist $\underline{\alpha}_a$ such that for all $\alpha_a > \underline{\alpha}_a$, references increase social welfare. The welfare-maximizing set of fees verifies*

$$f + F = 2min(\bar{F}, max(\underline{f}, f_0(k))), \tag{3.17}$$

with $f_0(k) \equiv \frac{1}{2k}((K + k)t_r - \alpha_a(K - k))$

Proof. Denote $\Delta W(k, f, F) \equiv W(k) - W(0)$ the increase in social welfare due to references. It follows that:

$$\begin{aligned}\frac{\Delta W(k,f,F)}{k} = \overbrace{\alpha_a}^{\text{more views}} - \overbrace{\frac{3t_r}{4}}^{\text{average extra distance}} - \overbrace{\frac{k}{K}q^*}^{\text{quality variation}} \\ + \overbrace{(f+F)\frac{K+k}{4ct_r}}^{\text{procompetitive fees}} + \overbrace{2c\frac{\alpha_a - (f+F)}{(4ct_r)^2}(\alpha_a(2K-k) + k(f+F))}^{\text{reduced cost of quality provision}}\end{aligned} \tag{3.18}$$

When α_a is arbitrarily large, the increment in welfare is positive. This proves the first part of the proposition. It results from (3.18) that:

$$\frac{1}{k}\frac{\partial W(k,f,F)}{\partial f} = \frac{K+k}{4ct_r} - \frac{\alpha_a(K-k) + k(f+F)}{4ct_r^2}, \tag{3.19}$$

Welfare-maximization relative to F results in the same relation. First-order conditions are $f + F = 2f_0(k)$ with $f_0(k) \equiv \frac{1}{2k}\left((K+k)t_r - \alpha_a(K-k)\right)$ and $\frac{\partial^2 W(k,f,F)}{\partial f^2} < 0$. This means $f + F = 2f_0(k)$ are candidate optimal fees. We need to ensure these fees belong to $\mathscr{F}$:

- if $f_0(k) < \underline{f}$, as is always the case when there is little differentiation ($t_r < \alpha_a$) and k is small, a social planner aims at relaxing competition and sets the smallest feasible fees $f = F = \underline{f}$.
- if $\underline{f} \leq f_0(k) \leq \bar{F}$, any feasible fees such that $f + F = 2f_0(k)$ maximizes welfare. This set is nonempty since $f = F = f_0(k)$ is feasible and meets the condition.
- if $f_0(k) > \bar{F}$, as is always the case when there is strong differentiation ($t_r > \alpha_a$) and k is small, $f = F = \bar{F}$ maximizes welfare.

□

The key result is that when platforms are sufficiently differentiated ($t_r > \alpha_a$) and k is not too large, it is always socially optimal that fees be set at the maximum level $f = F = \bar{F}$. It coincides with the fees that maximize quality and user surplus (see propositions 3.2 and 3.4, respectively).

6.2 Alternative market structures

In Proposition 3.3 we showed that a monopolistic go-between chooses fees so as to maximize its own profits. These fees differ from those that maximize the user, platform, or social surplus (Propositions 3.4, 3.5 and 3.6, respectively). In this section, we analyze how alternative market structures may affect fees.

6.2.1 Go-between is jointly owned by platforms

Many search engines manage references to their competitors themselves, without the help of an independent go-between (see Appendix A.1 for examples). This is formally equivalent to a setting when platforms jointly own the go-between. In that case reference fees are agreed upon with bilateral negotiations and platforms seek to maximize their joint profit. From Proposition 3.5, we find that this results in fees that maximize the platform surplus: $f = F = \underline{f}$.[15] This is also the set of fees that minimizes quality and

[15] When $\underline{f} = 0$, these low fees are formally similar to a "bill-and-keep" system in which the reciprocal reference fee is zero - that is, each platform agrees to display sponsored links from the other platform at no charge.

user surplus. We conclude that regulators should be wary of references that direct users to new external content, when these are operated without a third party.

6.2.2 Competition among independent go-betweens

Competition between go-betweens modifies the equilibrium set of fees. To show this, we assume that there is initially one incumbent go-between I who serves all platforms. As we showed in Proposition 3.3, in the absence of a threat of entry, I maximizes the reference fee margin: $f = \underline{f}$ and $F = \bar{F}$.

Now, a new go-between E considers entering the market. We denote by superscripts I and E respectively, the elements relative to the incumbent and the entrant. We assume the total number of clicks generated by a given go-between l is proportional to (1) the number of unique articles k on each platform, (2) the number of sponsors subscribed to go-between l, denoted by z_s^l, and (3) the number of publishers subscribing to go-between l, denoted by z_p^l.

In line with Caillaud and Jullien (2003), we assume that participants hold pessimistic beliefs, meaning that after a deviation of the entrant, participants expect zero market share for E, whenever possible. To attract participants even if they hold pessimistic beliefs, a new entrant has to adopt a divide-and-conquer strategy.

Our data show that many sponsors multi-home, i.e., newspapers may sponsor content within the pages of many other newspapers through the medium of more than one go-between. Therefore, it is relatively easy for the go-between to attract them. It suffices to post a price F^E such that the expected profit of a participating sponsor is nonnegative:

$$(\bar{F} - F^E) z_p^E \geq 0$$

Hence any price $F^E \leq \bar{F}$ would trigger adoption by all sponsors. E optimally sets $F^E = \bar{F}$. Equipped with such a sponsor fee, all sponsors are present in both platform I and E: $z_s^E = z_s^I = 1$. Contrary to sponsors, the vast majority of publishers single-home. A probable reason for this phenomenon is that space for ads in a website is limited and displaying more than one frame of sponsored content may cause excessive nuisance to readers. To attract publishers, E needs to post a publisher fee f^E slightly greater than f^I. The profit of the entrant is :

$$\Pi_E = (\bar{F} - f^E) z_s^E z_p^E \,,$$

with $z_s^E = \mathbb{1}_{F^E \leq \bar{F}}$ and $z_p^E = \mathbb{1}_{f^E > f^I}$. To ensure this expression is nonpositive and entry is deterred, I must set the publisher fees at the maximum feasible level $f^I = F^I = \bar{F}$. Hence the only equilibrium is a dominant-firm equilibrium in which only one go-between is active, captures all publishers and sponsors, and makes zero profits. Fees are set at the quality-maximizing level $f^I = F^I = \bar{F}$. Proposition 3.7 summarizes these findings.

Proposition 3.7 (Competition among go betweens)**.** *When there are no exclusive contracts and go-betweens charge interaction fees only, competition among several go-betweens results in fees being set at the quality-maximizing level.*

Proof. The proof derives from previous discussions. □

Appendix B.6 shows that introducing a richer set of pricing instruments induces a multiplicity of equilibria that may be detrimental to quality.

6.3 Policy implications

We have several results. First, if in the absence of a go-between all users multi-home ($s < \underline{s}$), the presence of a go-between always induces an increase in quality and user surplus. Indeed, the go-between allows for users to save on selection costs s. Furthermore, a simple comparison of quality in Proposition 3.1 (no go-between) and Proposition 3.2 (presence of a go-between) shows that the resulting quality $q(k)$ is at least as high as without a go-between $q^* \left(1 - \frac{k}{K}\right)$.

However, if visit costs are not too small ($s > \underline{s}$), resulting in no or only partial multi-homing, the presence of a go-between that charges low fees decreases equilibrium quality compared to the benchmark when the go-between is absent. A key result of the paper is that if interplatform reference fees are set too low, the user surplus is suboptimally low. When reference fees increase, R-users' utility increases. If the fees are sufficiently high, all users may be better off compared to a situation without a go-between. High fees increase social surplus when platforms are sufficiently differentiated but harm the platforms' profits. Figure 3.8 shows the feasibility set described in Lemma 2. The red dots show the pair (f, F) that maximizes the surplus of the labeled agents. Interplatform references materialize in the central, yellow triangle only.

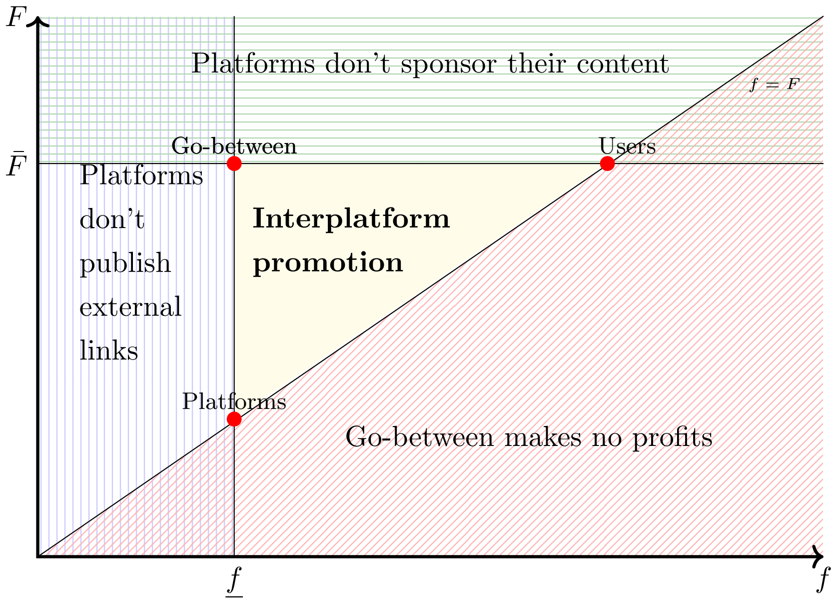
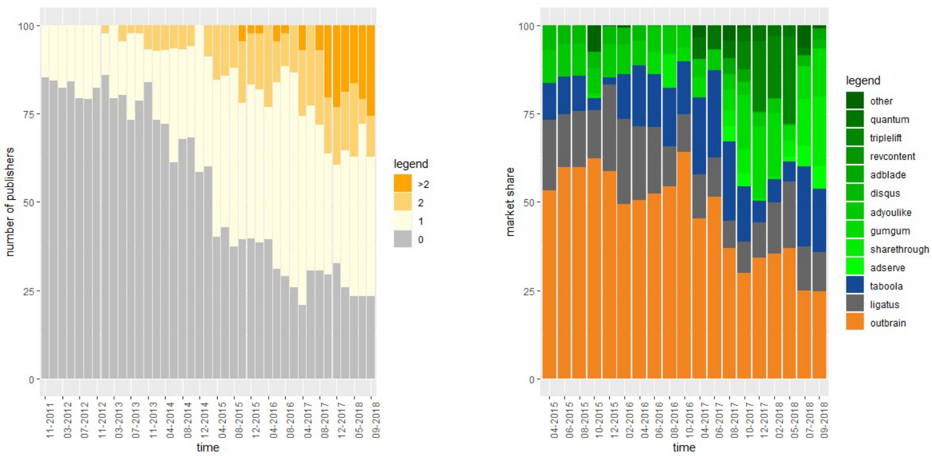


Figure 3.8: Feasibility set $\mathscr{F}$ (yellow, central triangle). Dots show the pair (f, F) that maximizes the surplus of the labeled agents.

From these positive results, we can derive rather straightforward policy implications. A policymaker willing to maximize web user surplus should aim at ensuring reference fees are as high as possible. This is true despite the marginal cost of producing interplatform references probably being very close to 0. Whereas direct regulation of such fees may be challenging, regulators may be able to encourage competition among go-betweens themselves: Section 6.2 shows that when go-betweens are restricted to charge usage fees f and F, competition among several go-betweens generates the set of fees that maximizes quality provision.

In many markets such as the search platforms exposed in Appendix A.1, platforms themselves act as go-betweens. In that case, interplatform referencing is a form of co-opetition in which ex ante bilateral negotiations result in small reference fees ($f = F = \underline{f}$). Closer to our lead application, Outbrain announced in 2018 its new premium service, "Sphere", which promotes high-quality editorial content only. Fees f and F are both set at USD 0.015/click, which is extremely low compared to reported cost-per-clicks in the range of USD 0.10-0.50/click on the standard service of Outbrain. Our paper argues that such low fees may be undesirable from a user- and social-welfare point of view. Regulators may need to step in and encourage intermediation by several market-based third parties so fees maximize equilibrium quality.

While assessing precisely the competitiveness of the intermediation market is beyond the scope of this paper, a few elements show that there is some competition among go-betweens. To illustrate this point, we collected historical data from HTTParchive.org, which periodically crawls the 450,000 top sites on the web and records detailed information about fetched resources, used web platform APIs, and other features. In particular, we can check whether news outlets' webpages included requests to content discovery platforms, on a bi-monthly basis since 2012. First, Figure 3.9a shows that an increasing number of publishers use more than just one go-between. This is good news as the possibility of multi-homing, as opposed to exclusive contracts, typically favors entry of new go-betweens. Second, Figure 3.9b shows that market shares vary over time, with a year-to-year switching rate of 25 percent. This means publishers' costs of switching go-between are sufficiently low for some switching to occur. This finding provides suggestive evidence that there is some competition among go-betweens. Assessing more precisely the degree of competition in this industry is, however, an important empirical question that is left for future research. Regulators should however be wary of the existence of exclusive contracts that may deter competition (see Appendix B.6).



(a) Number of content discovery platforms used per publisher (2011-18)

(b) Market shares of the three main content discovery platforms (2015-18)

Figure 3.9: Recent trends in adoption of content discovery platforms by publishers

7 Extensions

For the sake of concision, we relegate extensions to the Online Appendix, and only a brief summary is proposed here.

In Online Appendix OA.2 we allow for type-A users to have horizontal preferences for each platform. A smaller value of second impressions induces A-users to single-home. This framework is consistent with informative, as opposed to persuasive advertising. We show that all our results are qualitatively maintained. Further, we show that when both types of users single-home, references may impede the entry of a new platform. More precisely, in "Divide-and-Conquer" strategies where a side is attracted first, they make the "Divide" easier while rendering "Conquer" more difficult. The intuition is that references constitute a guarantee to first movers that they will keep interacting with the other side, even if the latter stays with the incumbent. Hence, references facilitate the migration of first movers. Conversely, second movers have less of an incentive to join the new platform, because references allow for the perpetuation of some interactions when each side is on a different platform. Which effect dominates depends on the size of network effects, and which side is attracted first. In our case, the second effect prevails and references impede entry. We also show that competition among go-betweens mitigates the entry-deterrence effect. This consideration reinforces our conclusion that regulators should ensure there is enough competition among go-between. We also allow for both usage fees and participation fees to be charged to A-users. A multiplicity of equilibria coexist. Our results are qualitatively maintained in each of them.

Online Appendix OA.3 considers the impact of interplatform references on the specialization of A-users. Indeed, some A-users may be especially interested in reaching users with strong preferences: advertisers selling football shoes tend to advertise on football, rather than basketball websites. We note that interplatform references lead to a homogenization of the usership of each platform. In turn, platforms may find it profitable to sell subscriptions to generalist A-users instead of specialized ones. This leads to a homogenization of users experience. Overall, the reduced differentiation leads to more intense competition and higher quality. Users with weak preferences are better off. However the impact on users with strong preferences is ambiguous.

Online Appendix OA.4 endogenizes the quantity of items produced. Mirroring our results on quality, we show that high fees always favor the creation of new content. Indeed, it increases the value of anchored users and, therefore, the incentives to attract them with more content. If fees are low, references trigger the creation of more content if and only if the equilibrium quality is not too high (i.e. c is not too small).

Online Appendix OA.5 notes that, in the media sector, go-betweens do not only serve quality recommendations. Actually, they have been widely criticized for circulating deceptive links known as "clickbait". We show that including quality recommendations helps go-betweens improve their reputation and pass the eligibility criteria for whitelisting by ad blockers. Hence we highlight a side effect of stringent whitelisting criteria, which is that it induces more business-sharing among producers of content. As we have seen, it may cause a general decrease in the quality of content, and in user surplus. Hence we unveil a novel channel through which ad blockers may decrease the overall quality of the world wide web.

We then consider some potential pro-competitive effects of references. In the body of the article, we assume that the go-between directs users only to new content the initial platform did not have. This is consistent with our empirical findings (Appendix 3) and the affirmed objective of content discovery platforms to induce more traffic, rather than substitute the traffic of publishers towards other content producers. However, in some sectors references may direct to content that constitute an overlap with the content of the initial platform: Online Appendix OA.6 considers the effect of referencing towards substitute content. It shows that a pro-competitive effect appears. However, these links create less value than those directing towards new content. Go-betweens are therefore likely to prefer the latter over the former. We show that in our setting with perfect information, linking to perfect substitutes from competitors is never individually rational, unless reciprocity is contracted ex-ante. Such a coordination, however, induces a decrease in quality, user and social welfare.

This article assumes perfect information. Online Appendix OA.7 relaxes this assumption and assumes some users are uninformed about the quality of each platform. They are therefore willing to experiment the content of various platforms. Hence, publishers have an incentive to direct them to low-quality foreign content so as to misguide them into believing the competitor is of poor quality. Doing so, they harvest the publisher fees while keeping most users anchored. This result may explain why our results in Table 3.2 reveal that sponsored articles are typically older if they are issued by a competing news outlet, rather than another news outlet of the same press group.

8 Conclusion

We showed that references between platforms, even though they may be ex post efficient (users enjoy more diverse content), may turn out to be undesirable once ex ante considerations are taken into account. Indeed, we showed that references decrease platforms' incentives to attract anchored users: they become less precious to platforms, since a "lost" user can still roam to the local platform through references. In turn, quality decreases. This research casts a doubt on the desirability of these links often labeled –ironically– "content you may like" in the media industry.

There is however a bright side. Reference fees, if present, increase the value derived from anchored users and decrease the value of roamers. Therefore, it increases platforms' incentives to invest in quality and attract anchored users instead of roamers. In turn, it increases user and social surplus. A clear policy implication is that reference fees should be set as high as possible–under the constraint that both the sponsor and publisher accept these links. This conflicts with the interests of the contracting parties – go-betweens want a large fee mark-up whereas platforms want both fees to be small. Competition among go-betweens induces the quality-maximizing set of fees. Regulators should therefore continuously monitor the market for intermediation between platforms and ensure there is sufficient competition.

We took online media as a lead example because interplatform references are frequent and largely unregulated. Furthermore, the mediation by third parties raised important questions. However, this formal model has a broader reach. It readily applies to other industries in which platforms may share a side of their business with competitors. Search engines for flights tickets, car rentals or hotel rooms often list competitor results together with their own, or provide tools to conveniently compare their results with those of competitors. Similarly to our media application, the direct effect of such references between competing platforms is that users enjoy more diverse content. For users to be better off in the long run, however, reference fees must be high: if a prospective user navigating on her favorite search engine finally clicks on a sponsored link, the sponsor should pay a fee to the initial platform. Failing that, and, in particular, if reference fees are agreed upon after bilateral negotiation between platforms (e.g. bill-and-keep), interplatform references result in a decrease in quality and a decrease in user welfare.

An important question not directly treated in this paper, is the impact of sponsored content on political polarization. A phenomenon of echo chambers on the web has raised increasing concerns in the past few years (Flaxman et al. (2016); Garrett (2009); Gentzkow and Shapiro (2010); Gentzkow and Shapiro (2011)). Our paper shows that sponsored content encourages readers to also visit their platforms of second choice – thereby exiting their echo chamber. Modeling the welfare benefits of this feature of the model was beyond the scope of the present paper but certainly is an interesting alley for future research.

Bibliography

Allcott, H. and Gentzkow, M. (2017). Social Media and Fake News in the 2016 Election. *Journal of Economic Perspectives.*

Ambrus, A., Calvano, E., and Reisinger, M. (2016). Either or both competition: A "two-sided" theory of advertising with overlapping viewerships. *American Economic Journal: Microeconomics*, 8(3):189–222.

Anderson, S. P., Foros, Ø., and Kind, H. J. (2017). Product Functionality, Competition and Multipurchasing. *International Economic Review.*

Armstrong, M. (1998). Network interconnection in telecommunications. *Economic Journal.*

Armstrong, M. (1999). Competition in the Pay-TV Market. *Journal of the Japanese and International Economies.*

Armstrong, M. (2006). Competition in two-sided markets. *The RAND Journal of Economics*, 37(3):668–691.

Armstrong, M. and Wright, J. (2007). Two-Sided Markets, Competetive Bottlenecks and Exclusive Contracts: Research Article. *Economic Theory*, 32(November):353–380.

Athey, S., Calvano, E., and Gans, J. S. (2012). The Impact of the Internet on Advertising Markets for News Media. *SSRN Electronic Journal*, (July).

Belleflamme, P. and Peitz, M. (2018). Platform competition: Who benefits from multihoming?

Berry, S. and Waldfogel, J. (2010). Product quality and market size. *Journal of Industrial Economics.*

Blei, D. M., Ng, A. Y., and Jordan, M. I. (2003). Latent Dirichlet Allocation. *Journal of Machine Learning Research.*

Cage, J. (2017). Media Competition, Information Provision and Political Participation: Evidence from French Local Newspapers and Elections, 1944-2014.

Cagé, J., Hervé, N., and Viaud, M.-L. (2016). The Production of Information in an Online World: Is Copy Right?

Caillaud, B. and Jullien, B. (2003). Chicken & Egg: Competition among Intermediation Service Providers. *The RAND Journal of Economics*, 34(2):309–328.

Calzada, J. and Gil, R. (2016). What Do News Aggregators Do? Evidence from Google News in Spain and Germany.

Calzada, J. and Ordóñez, G. (2012). Competition in the News Industry: Fighting Aggregators with Versions and Links. *NET Institute Working Paper*, No. 12-22.

Calzada, J. and Tselekounis, M. (2018). Net Neutrality in a hyperlinked Internet economy. *International Journal of Industrial Organization*.

Chiou, L. and Tucker, C. (2011). How Does Content Aggregation Affect Users ' Search for Information ? *Online*, (October).

Dellarocas, C., Katona, Z., and Rand, W. (2013). Media, Aggregators, and the Link Economy: Strategic Hyperlink Formation in Content Networks. *Management Science*, 59(19):2360–2379.

Doganoglu, T. (2003). Dynamic price competition with consumption externalities. pages 43–69.

Drago, F., Nannicini, T., and Sobbrio, F. (2014). Meet the press: How voters and politicians respond to newspaper entry and exit. *American Economic Journal: Applied Economics*.

Evans, D. S. and Schmalensee, R. (2016). Matchmakers: The New Economics of Multisided Platforms. *Harvard Business School Press Books*.

Fafchamps, M. and Gubert, F. (2007). The formation of risk sharing networks. *Journal of Development Economics*.

Flaxman, S., Goel, S., and Rao, J. M. (2016). Filter bubbles, echo chambers, and online news consumption. *Public Opinion Quarterly*.

Garrett, R. K. (2009). Echo chambers online?: Politically motivated selective exposure among Internet news users. *Journal of Computer-Mediated Communication*.

Gentzkow, M. and Shapiro, J. M. (2010). What Drives Media Slant? Evidence from U.S. Daily Newspapers.

Gentzkow, M. and Shapiro, J. M. (2011). Ideological segregation online and offline. *Quarterly Journal of Economics*.

Gentzkow, M., Shapiro, J. M., and Sinkinson, M. (2011). The effect of newspaper entry and exit on electoral politics. *American Economic Review.*

George, L. M. and Hogendorn, C. (2012). Aggregators, search and the economics of new media institutions. *Information Economics and Policy*, 24(1):40–51.

Hagiu, A. (2006). Pricing and commitment by two-sided platforms. *The RAND Journal of Economics*, 37(3):720–737.

Hamilton, J. (2006). All the News That's Fit to Sell: How the Market Transforms Information Into News.

Jeon, D. S. and Nasr, N. (2016). News aggregators and competition among newspapers on the internet. *American Economic Journal: Microeconomics*, 8(4):91–114.

Katona, Z. and Sarvary, M. (2008). Network Formation and the Structure of the Commercial World Wide Web. *Marketing Science*, 27(5):764–778.

Kozinets, R. V. (2008). Journal of Marketing Research. *Journal of Marketing Research*, 45(1):i–ii.

Le Guellec, M. (2016). *Presse et culture dans l'Espagne des Lumières*. Bibliothèq edition.

Ma, L. (2010). A Dynamic Competitive Analysis of Content Production and Link Formation of Internet Content Developers. *Working paper*, (September).

Markovich, S. (2008). Snowball : A dynamic oligopoly model with indirect network effects \$. 32(98):909–938.

Mayzlin, D. and Yoganarasimhan, H. (2012). Link to Success: How Blogs Build an Audience by Promoting Rivals. *Management Science*, 58(9):1651–1668.

McFadden, D. (1978). Modelling the choice of residential location.

Mitchell, M. F. and Skrzypacz, A. (2006). Network externalities and long-run market shares. pages 621–648.

Ofcom (2014). News consumption in the UK 2015. (December):1–12.

Parker, G. and Van Alstyne, M. (2005). Two-Sided Network Effects: A Theory of Information Product Design. *Management Science*, 51(10):1494–1504.

Purcell, K., Rainie, L., Mitchell, A., Rosenstiel, T., and Olmstead, K. (2010). Understanding the Participatory News Consumer. *Pew Internet {&} American Life Project.*

Reisinger, M. (2014). Two-part tariff competition between two-sided platforms. *European Economic Review.*

Rochet, J.-C. and Tirole, J. (2003). Two-Sided Markets. *Journal of the European Economic Association*, pages 990–1029.

Tullock, G. (1980). Efficient rent seeking. In *Toward a Theory of the Rent-Seeking Society.*, pages 97–112.

A Documenting interplatforms referencing

A.1 Referencing of competitors on the Web

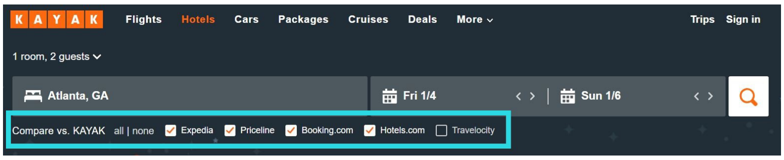


Figure 3.10: Kayak hotel search (subsidary of Booking group) directs to competitor Expedia.com and Expedia subsidiaries Hotel.com and Travelocity.

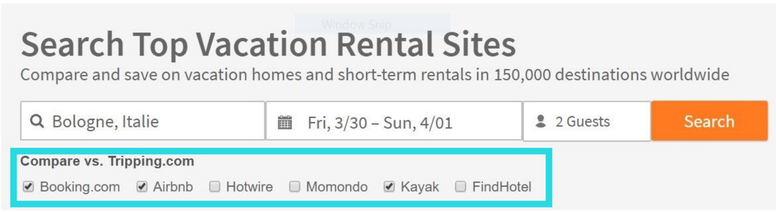


Figure 3.11: Tripping.com directs users towards competitors Booking.com and Kayak

Figure 3.12: TripAdvisor directs users towards competitors Expedia.se, Hotels.com and Booking.com

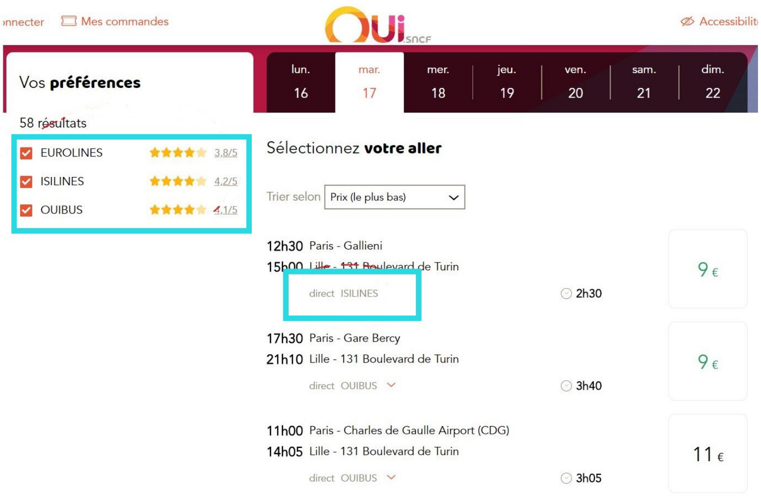


Figure 3.13: SNCF lists its Ouibus subsidiary for intercity bus trips together with listings from competitors Isilines and Eurolines

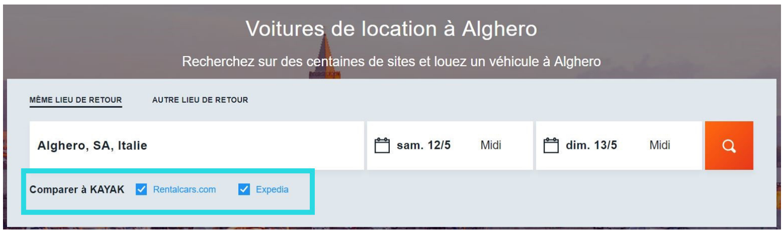


Figure 3.14: Kayak car rental services directs to competitor Expedia.com

A.2 Referencing of competitors in the media industry

Referrals to competitors is not a new phenomenon in the media industry. One may even claim that the media industry was born with such referrals. Le Guellec (2016) is very instructive about this point. The author notices that already in the 18th century, freshly born literary journals would persistently refer to one another in their publications. It could take the form of what we would today call “referee reports” on competitors’ articles, replication of content, but also outright publicity for other journals. At a period when the press was highly specialized, and only a limited group of people had access to information, this was seen as a way to increase own quality and overall readership, without risking to lose readers. These interplatform references have largely persisted over time. Cagé et al. (2016) estimate that 70% of the documents in the sample of French news media they collected in 2013 present at least some external copy.

Closer to our precise application, the New York Times published in 2006 an article named "Platforms to Use Links to Rivals on Web Sites".[16] The article discusses the emergence of content discovery platforms. It describes the displaying of news from competitors as a new phenomenon, meant to be a response to the competitive pressure induced by news aggregators. The article also stressed that these links provide diversity to readers and keep them connected for a longer period. It also notes that "these deals are but one indication that platforms may be reconsidering long-held beliefs about how to compete, and cooperate, with other publishers", a statement we substantiate in the present paper.

A reason for the growing popularity of native ads such as those of content discovery platforms is that they are less frustrating to users than other types of advertisement, and may therefore be whitelisted by ad blockers. PageFair, a company that helps websites regain revenue lost from ad blockers, reported in 2017 a stable 30 percent global growth year-over-year in ad blocker usage, with over 600 million device blocking ads.[17] Most alarming to advertisers is that 74 percent of ad blocker users say they leave websites that have a wall against ad blockers. However, 77 percent of ad blocker users are willing to view *some* ad formats. This is why the main ad blockers have a policy that whitelists "acceptable ads", according to criteria ensuring these ads do not decrease user experience excessively. If they meet the criteria, advertisers can pay the ad blocker to be included in the whitelist. The fee amounts to 30% of revenues generated by the whitelisting.[18] The fact that the advertisement market attributes substantial value to nonintrusive ads may explain the success of content discovery platforms.

In 2018, one of the major content discovery platforms, Taboola, boasted it reached 1.4 billion people per month, which equates to around half of global web users. The company projects to triple its revenues to $1 billion in 2018, compared to 2015.[19] Outbrain.com is Taboola's main competitor. Similarly to Taboola, it states its mission is to "Help people discover content that they can trust to be interesting, relevant and timely for them".[20] The sponsored content is usually displayed at the end of the publishers' article, with the title of the sponsored content and an illustration. Figures 3.15 and 3.16 provide examples of sponsored links distributed by a content discovery platform.

[16] See http://www.nytimes.com/2006/07/31/technology/31ecom.html

[17] https://pagefair.com/downloads/2017/01/PageFair-2017-Adblock-Report.pdf

[18] https://adblockplus.org/acceptable-ads

[19] See https://blog.taboola.com/taboola-2017-year-in-review/ and https://www.mediapost.com/publications/article/315630/ projects-1-bil-in-2018-cites-expanded-re.html

[20] See http://www.outbrain.com/uk/about/company

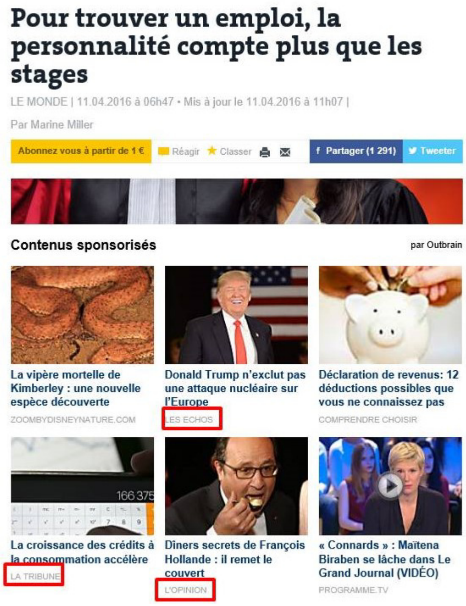


Figure 3.15: Le Monde (desktop)

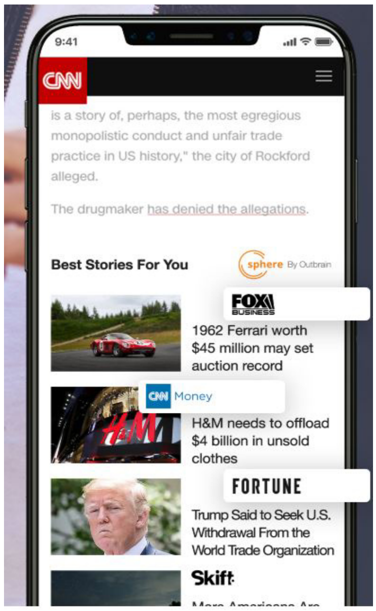


Figure 3.16: CNN (mobile)

Figure 3.15 and 3.16: illustrative screen captures of Outbrain widgets.

Traffic is remunerated on a per-click basis. Sponsors pay a fee per click that depends on the quality of the targeted audience (clicks from an audience composed of high-value targets would be charged a higher price). In practice, fees are set following a generalized first price auction. Several bidders (the sponsors) compete for a limited number of slots. They bid the cost-per-click (CPC) they intend to pay to the content discovery platform. The latter compute a quality score for each piece of content. It is based on, among other measures, its expected click-through-rate (CTR). The product of CPC and the quality score gives a measure similar to Google's Ad Rank. The bidder with the highest Ad Rank gets the first slot, the second-highest, the second slot and so on. Some of the revenue generated by these auctions is then paid back to the publisher. The quality score includes other elements than just the CTR, such as editorial quality of content. This means content discovery platforms effectively decide the quality and type of content they display.

We note that both the publisher and the sponsor have a veto right regarding which content they want to display: the guidelines of Outbrain state that "Direct competitors cannot promote negative earned media or content that defames or otherwise compromises an industry or competitor without clear disclosure".[21]

[21] See http://www.outbrain.com/fr/amplify/guidelines : " our distribution partners may choose to

Even though recommendations may allow the user to dig deeper into a topic, there is evidence that instead of providing closely related content, Outbrain tends to suggest "popular" links on unrelated topics, or content tailored to user behavior. Outbrain claims it "provides people with the magical experience of serendipity similar to the one they get when flipping through the pages of a favorite magazine or newspaper".[22] Similarly, Taboola describes itself as a "search engine in reverse": instead of expecting people to find information, information should find people wherever they may be. This means content discovery platforms are likely to provide new content, rather than duplicated information.[23]

In 2018, Outbrain general manager for the US Matt Crenshaw declared that "publishers used to think of each other as competitors, but now they have indicated to Outbrain they would like more opportunities to lean on each other".[24] In the present paper we show that this "leaning" can have anti-competitive effects. Interestingly, some hints of our results were present in early declarations of Oubrain CEO Yaron Galai. In 2011, he declared that "Microsoft link exchange wasn't much of an inspiration because having links being reciprocal eventually will create a slippery slope of quality going down. I don't believe reciprocal links can achieve good recommendations".[25]

B Omitted Proofs

B.1 Proof of Proposition 3.1

We first look for candidate equilibria.

Candidate equilibria with full multi-homing

We first study the case of full multi-homing. We start with the extreme case when $s = 0$. In that case, all R-users multi-home and the equilibrium quality is such that small variations of quality do not affect the extent of multi-homing. With $n_r^{i,MH} = n_r^i$,

block specific pages or entire sources"

[22]https:outbrain.com/blog/you-are-what-you-recommend-value-of-trust/

[23]Content discovery platforms claim they recommend content that is new to users: "Les liens affinitaires sont ceux qui performent le moins", says Franck Mansouret, Outbrain's country manager for France. http://www.e-marketing.fr/Thematique/Medias-1006/Web-Mobile-10031/Breves/Avec-Outbrain-la-data-pilote-les-newsrooms-236436.htm

[24]https://martechtoday.com/outbrain-launches-sphere-platform-content-recommendations-premium-publishers-211097

[25]See https://www.youtube.com/watch?v=Hod1FEgy8Tk

one can show that quality falls to :

$$q(k) = q^* - \frac{\alpha_a k}{4ct_r} \tag{A3.20}$$

This can however be sustained as an equilibrium if and only if incremental surplus from roaming exceeds the gains in visit costs, for all users:

$$s \leq k\left(\frac{\alpha_a(K-k)}{4ct} - t_r\right) \equiv \underline{\underline{s}}$$

When s exceeds $\underline{\underline{s}}$, platforms can set quality such that the market for roamers is just covered: $n_r^{i,MH} = n_r^i$, which translates in:

$$q_s = \frac{s}{k} + t_r \tag{A3.21}$$

With such quality, a marginal increase in quality results in more anchored users but not more roamers:

$$\frac{\partial \pi}{\partial q}(q_s^+) = \frac{\alpha_a(K-k)}{2t_r} - 2cq_s < 0$$

An $\epsilon > 0$ decrease in quality generates a loss of $\frac{\epsilon}{t_r}$ roamers, who are worth $\alpha_a k$ each:

$$\frac{\partial \pi}{\partial q}(q_s^-) = \frac{\alpha_a K}{2t_r} + \frac{\alpha_a k}{t_r} - 2cq_s > 0$$

This means that any local deviation from q_s results in a decrease in profits. It is easy to show that large deviations also result in a decrease in profits.

The second inequality holds as long as $q_s < q^*\left(1 + \frac{k}{K}\right)$: indeed, if s is sufficiently large, it becomes optimal to let some users single-home. Single-homing does not arise if and only if users located at the extremities of the Hotelling line derive positive surplus from a second visit:

$$s < k\left(q^*\left(1 + \frac{k}{K}\right) - t_r\right) \equiv \underline{s}$$

Candidate equilibria with partial multi-homing

If $s \geq \underline{s}$, some R-users –those with strong preferences– start single-homing. The number $n_r^{j,MH}$ of multi-homers anchored with j is derived from the R-users just indifferent between single- and multi-homing. This means we search for x such that $u_r^{i,j}(x,k) = 0$.

We derive that

$$n_r^{j,MH}(q_i, q_j) = \frac{1}{t_r}\left(q_i - \frac{s}{k}\right) - n_r^i(q_i, q_j) \tag{A3.22}$$

The expected profits of platform i are:

$$\begin{aligned}\Pi_i(q_i, q_j) &= \alpha_a V^i - c_i q_i^2 \\ &= \alpha_a \left(n_r^i K + n_r^{j,MH} k\right) - c_i q_i^2\end{aligned}$$

Solving for a symmetric equilibrium, we find that equilibrium quality when multi-homing is only partial is greater than q^*:

$$q(k) = q^*\left(1 + \frac{k}{K}\right), \tag{A3.23}$$

and there are $m(s) = n_r^{i,MH} + n_r^{j,MH} = \frac{2}{t_r}\left(q_i - \frac{s}{k}\right) - 1$ multi-homers. We observe that equilibrium quality is greater than when all R-users single-home. The intuitive explanation is as follows. On the one hand, multi-homing makes fringe anchored users less valuable, relative to fringe non-anchored users: a lost anchored user is a multi-homer who visits the platform even if she anchors with the competitor. This decreases equilibrium quality. On the other hand, platforms also try to attract marginal multi-homers, which increases quality. In our setting the second effect prevails.

Partial multi-homing can be sustained as long as R-users with weak preference multi-home, while users with strong preferences single-home:

$$\underline{s} \equiv k\left(q^*\left(1 + \frac{k}{K}\right) - t_r\right) \leq s \leq k\left(q^*\left(1 + \frac{k}{K}\right) - \frac{t_r}{2}\right) \equiv \overline{\overline{s}}^*$$

Candidate equilibria with full single-homing

We now explore the case in which s is so large that $u_r^{i,j}(x, k)$ is always negative. This results in no multi-homing $n_r^{j,MH} = 0$ and $V^i = Kn_r^i$. Solving for the indifferent R-user (3.6), we obtain the demand function:

$$n_r^i = \frac{1}{2} + \frac{q_i - q_j}{2t_r}$$

Simple calculations show that as long as A1 holds, there is always a unique Nash equilibrium, and it is symmetric. Equilibrium quality is :

$$q^* = \frac{\alpha_a K}{4ct_r} \tag{A3.24}$$

A paradigm with no multi-homing can be sustained as long as all users derive negative surplus from a second visit : $s \geq k\left(q^* - \frac{t_r}{2}\right) \equiv \bar{s}^*$. We observe that $\bar{s}^* < \bar{\bar{s}}^*$. When $s \in [\bar{s}^*, \bar{\bar{s}}^*]$, there are therefore two candidate equilibria.

Equilibrium

Regions with a unique candidate equilibrium

For each s in the set $\{s \in [0, \bar{s}^*[\cup]\bar{\bar{s}}^*, +\infty)\}$, there is a unique candidate Nash equilibrium. It is easy to show that the candidate equilibrium qualities are strictly dominant strategies. For each s in this set, there is therefore a unique Nash equilibrium, and it is pure:

- for $s \leq \underline{\underline{s}}$: there is full multi-homing. The equilibrium quality is given in (A3.20)
- for $\underline{\underline{s}} \leq s < \underline{s}$: there is full multi-homing. The equilibrium quality is given in (A3.21)
- for $\underline{s} \leq s < \bar{s}^*$: there is partial multi-homing, which magnitude is given by in (A3.22). The equilibrium quality is given in (A3.23)
- for $s > \bar{\bar{s}}^*$: there is full single-homing. The equilibrium quality is given in (A3.24)

We now treat the case when $s \in [\bar{s}^*, \bar{\bar{s}}^*]$.

Region with two candidate equilibria

When $s \in [\bar{s}^*, \bar{\bar{s}}^*]$, there are two candidate equilibria in pure strategies: one with full single-homing, and one with partial multi-homing. We can show that all quality choices are dominated by either or both q^* and $q^*\left(1 + \frac{k}{K}\right)$. Hence the choice set of each platform is reduced to a binary choice between low (l) and high (h) quality. Denote $\Pi_i(b_i, b_j)$ the profit of platform i when platform i chooses quality b_i and platform j chooses quality b_j. To find the Nash equilibria of the game, we write it in normal form:

		Platform 2	
		high	*low*
Platform 1	*high*	$(\Pi_1(h,h), \Pi_2(h,h))$	$(\Pi_1(h,l), \Pi_2(h,l))$
	low	$(\Pi_1(l,h), \Pi_2(l,h))$	$(\Pi_1(l,l), \Pi_2(l,l))$

We denote $\bar{s} \equiv k\left(\frac{\alpha_a}{4ct_r}\left(K + \frac{k}{4}\right) - \frac{t_r}{2}\right)$ and $\bar{\bar{s}} \equiv k\left(\frac{\alpha_a}{4ct_r}\left(K + \frac{3k}{4}\right) - \frac{t_r}{2}\right)$. We have that $\bar{s}^* < \bar{s} < \bar{\bar{s}} < \bar{\bar{s}}^*$. We recall that :

$$\begin{aligned}
\Pi_i\left(q^*, q^*\right) =& \frac{\alpha_a K}{2} - c\left(q^*\right)^2 \\
\Pi_i\left(q^*\left(1+\frac{k}{K}\right), q^*\left(1+\frac{k}{K}\right)\right)) =& \frac{\alpha_a K}{2} + \alpha_a k n_r^{j,MH}\left(q^*\left(1+\frac{k}{K}\right), q^*\left(1+\frac{k}{K}\right)\right) \\
& - c\left(q^*\left(1+\frac{k}{K}\right)\right)^2 \\
\Pi_i\left(q^*\left(1+\frac{k}{K}\right), q^*\right) =& \frac{\alpha_a K}{2} + \frac{q^*\alpha_a k}{2t_r} + \alpha_a k n_r^{j,MH}\left(q^*\left(1+\frac{k}{K}\right), q^*\right) \\
& - c\left(q^*\left(1+\frac{k}{K}\right)\right)^2 \\
\Pi_i\left(q^*, q^*\left(1+\frac{k}{K}\right)\right) =& \frac{\alpha_a K}{2} - \frac{q^*\alpha_a k}{2t_r} + \alpha_a k n_r^{j,MH}\left(q^*, q^*\left(1+\frac{k}{K}\right)\right) \\
& - c\left(q^*\left(1+\frac{k}{K}\right)\right)^2,
\end{aligned}$$

where we have used the demand function (3.9), resulting in $n_r^i\left(q^*\left(1+\frac{k}{K}\right), q^*\right) = \frac{1}{2} + \frac{q^*k}{2Ktr}$. $n_r^{j,MH}(q_i, q_j)$ is given by (A3.22). Simple calculations show that $\Pi_i(l,l) > \Pi_i(h,l)$ if and only if $s > \bar{s}$. $\Pi_i(h,h) > \Pi_i(l,h)$ if and only if $s < \bar{\bar{s}}$.

Hence if $s > \bar{\bar{s}}$, the unique Nash equilibrium is (l,l). If $s < \bar{s}$, the unique Nash equilibrium is (h,h). When $\bar{s} \leq s \leq \bar{\bar{s}}$, we have that $\Pi_i(h,h) \geq \Pi_i(l,h)$ and $\Pi_i(l,l) \geq \Pi_i(h,l)$. Hence both (l,l), which induces full single-homing, and (h,h), which induces full multi-homing, are Nash equilibria. This completes the proof of Proposition 3.1.

We note that there may be an equilibrium in mixed strategies. We denote μ_i the probability that platform i chooses the high quality $q^*\left(1+\frac{k}{K}\right)$. $1-\mu_i$ is the probability that platform i chooses the low quality q^*. If μ_j is a best response of j, both high and low quality must be a best response to i's choice:

$$\mu_i \Pi_j(h,h) + (1-\mu_i)\Pi_j(l,h) = \mu_i \Pi_j(h,l) + (1-\mu_i)\Pi_j(l,l)$$
$$\Leftrightarrow \mu_i = \frac{\Pi_j(l,l) - \Pi_j(l,h)}{\Pi_j(h,h) + \Pi_j(l,l) - \Pi_j(h,l) - \Pi_j(l,h)} \tag{A3.25}$$

When $s \in]\bar{s}, \bar{\bar{s}}[$, we can show that $\mu_i \in]0,1[$, which means there exists a non-degenerate equilibrium in mixed strategies.

B.2 Proof of Proposition 3.2

B.2.1 Multi-homing advertisers

We generalize the setting of Section 5 to general, asymmetric cost functions. Each platform i has cost parameter $C_i(q_i) > 0$. The profits of platform i is:

$$\Pi(q_i, q_j) = \alpha_a \left(K n_r^i + k(1-n_r^i)\right) + k\left(f n_r^i - F(1-n_r^i)\right) - C_i(q_i)$$

Using the demand function (3.9), the first-order conditions with respect to q_i yields:

$$\frac{\partial C_i}{\partial q_i}(q_i, k) = \frac{\alpha_a K}{2t_r} - k\frac{\alpha_a - f - F}{2t_r} = \frac{\partial C_i}{\partial q_i}(q_i, 0) - k\frac{\alpha_a - f - F}{2t_r} \tag{A3.26}$$

If $C_i(.)$ is convex, the second order derivatives are negative, meaning a maximum is reached. Taking symmetric, quadratic costs $C_i(q) = cq^2$ results in relation (3.11).

To ensure that the market is covered, we verify that all users derive nonnegative surplus from viewing a relevant item of any of the two platform : $q_i \geq t_r$. With quadratic costs, this requires that $c_1, c_2 \leq \frac{\alpha_a K - k(\alpha_a - f - F)}{4t_r^2}$, which reduces to Assumption A1 when costs are symmetric.

Furthermore, $\frac{\partial^2 \Pi_i}{\partial c_i \partial k} = -2c_i q_i \frac{\partial q_i}{\partial k}$. If fees are low, $\frac{\partial^2 \pi}{\partial c_i \partial k} > 0$, which means that references benefit especially platforms with high costs of quality provision. We note that q_i does not depend on c_j. Hence all the qualitative results of the following propositions 3.1 to 3.7 are maintained.

B.2.2 Single-homing advertisers

We generalize the setting of Online Appendix OA.2 to non symmetric costs. Each platform i has cost parameter $c_i > 0$. Denote for concision $\Delta(k) \equiv t_r t_a - \alpha_r \alpha_a (K - k)$

Starting from profit function (3.5), we can re-write the equilibrium quality and prices as:

$$2c_iq_i = \alpha_a(K-k)\frac{p_i}{2\Delta(k)} + (f+F)k\frac{t_a}{2\Delta(k)} \tag{A3.27}$$

$$p_i\frac{t_r}{2\Delta(k)} = -\frac{\alpha_r}{2\Delta(k)}(f+F)k + \left(\frac{1}{2} + \frac{\alpha_a(K-k)(q_i-q_j)+t_r(p_j-p_i)}{2\Delta(k)}\right) \tag{A3.28}$$

Inserting (A3.27) into (A3.28), we find that

$$p_i + p_j = \frac{2\Delta(k)}{t_r} - (f+F)k\frac{2\alpha_r}{t_r}$$

The sum of prices posted by platforms (and hence at least one of these prices) increase with k, when fees f and F are small. Taking fees as high as possible reduces or even may reverse this effect. Unravelling further the calculations, we find that

$$p_i = \frac{1}{t_r}\frac{2\Delta(k)-(f+F)k2\alpha_r}{1+\frac{\frac{(\alpha_a(K-k))^2}{2\Delta(k)c_i}-t_r}{\frac{(\alpha_a(K-k))^2}{2\Delta(k)c_j}-t_r}} \tag{A3.29}$$

From (A3.29) and (A3.27) we find that in accordance with intuition price increases and quality decreases as c_i increase. Using the envelope theorem on each platform's objective function (3.5) we have that:

$$\frac{\partial\Pi_i}{\partial c_i} = -q_i^2 < 0$$

When fees are high, the conclusions are reversed.

B.3 Proof of Lemma 1 and Lemma 2

Lemma 1 (perfect information): We first allow for both platforms to be perfectly rational. We assume that the go-between sells a unidirectional sponsoring service, i.e., allows for a situation where platform j would sponsor content in platform i but not the other way around. We look for feasible fees f and F such that unilateral sponsoring is accepted by both parties. We assume that s is large enough so that there is no multi-homing.

We saw in the main text that all A-users multi-home and all their surplus is extracted by platforms, as shown in Armstrong and Wright (2007). This means we always have that $\gamma_i = \alpha_a$. When only j sponsors content in i, R-user utility is :

$$U_r^i(x,k) = \bar{u}_r + (q_i - t_r \mid x - x_i \mid)K + (q_j - t_r \mid x - x_j \mid)\, k \tag{A3.30}$$
$$U_r^j(x,k) = \bar{u}_r + (q_j - t_r \mid x - x_j \mid)K \tag{A3.31}$$

From these utility functions we derive the demand function:

$$n_r^i(k) = \frac{K-k}{2K-k} + \frac{(q_i - q_j)K + q_j k}{t_r(2K-k)} \tag{A3.32}$$

The platforms' profit functions are:

$$\begin{aligned}
\Pi_i(q_i) =& \alpha_a K n_r^i + f k n_r^i - c q_i^2 \\
\Pi_j(q_j) =& \alpha_a (K n_r^j + k n_r^i) - F k n_r^i - c q_j^2 \,,
\end{aligned}$$

from which we derive that:

$$\begin{aligned}
2cq_i =& (\alpha_a K + fk)\frac{\partial n_r^i}{\partial q_i} \\
=& (\alpha_a K + fk)\frac{K}{t_r(2K-k)} \\
2cq_j =& \alpha_a K \frac{\partial n_r^j}{\partial q_j} + k(\alpha_a - F)\frac{\partial n_r^i}{\partial q_j} \\
=& (\alpha_a K - k(\alpha_a - F))\frac{K-k}{t_r(2K-k)}
\end{aligned}$$

It reduces to :

$$q_i(k,f) = q^* \left(\frac{(1 + \frac{fk}{\alpha_a})K}{K - \frac{k}{2}} \right) \tag{A3.33}$$
$$q_i(k,F) = q^* \left(\frac{\left((1 - k\left(1 - \frac{F}{\alpha_a}\right)\right)(K-k)}{K - \frac{k}{2}} \right) \tag{A3.34}$$

We can compute the equilibrium profits when there are k references:

$$\Pi_i^*(k,f,F) = \Pi_i^*(0) + \alpha_a K(n_r^i(k) - n_r^i(0)) + kfn_r^i(k) + c(q_i^2(0) - q_i^2(k))$$
$$\Pi_j^*(k,f,F) = \Pi_j^*(0) - \alpha_a K(n_r^i(k) - n_r^i(0)) + k(\alpha_a - F)n_r^i(k) + c(q_j^2(0) - q_j^2(k))$$

Define $P(k,f,F) \equiv \Pi_i^*(k,f,F) - \Pi_i^*(0)$ and $S(k,f,F) \equiv \Pi_j^*(k,f,F) - \Pi_j^*(0)$. The feasible set is all pairs (f, F) such that $P(k, f, F) \geq 0$, $P(k, f, F) \geq 0$ and $f \leq F$. We can verify that $f = F = -\alpha_a$ satisfies all three conditions, thereby proving the non-emptiness of $\mathscr{F}$ (Lemma 1):

$$P(k, -\alpha_a, -\alpha_a) = \alpha_a K(n_r^i(k) - n_r^i(0)) + kfn_r^i(k) + c(q_i^2(0) - q_i^2(k, f)) \geq 0$$

The inequality follows from the fact that for k small enough, $(K - k)n_r^i(k) - \frac{K}{2} \geq 0$, $q_i^2(k, -\alpha_a) < q^*$. Similarly, we can show that $S(k, -\alpha_a, -\alpha_a) \geq 0$. Further, we have that

$$\begin{aligned} \frac{\partial P(k, f, F)}{\partial f} &= kn_r^i(k) > 0 \\ \frac{\partial S(k, f, F)}{\partial F} &= -kn_r^i(k) < 0 \end{aligned}$$

Given that taking f arbitrarily low results in $P(k, f, F) < 0$ and F arbitrarily high results in $S(k, f, F) < 0$, we conclude that $\mathscr{F}$ is bounded. This completes the proof of Lemma 1.

$P(k, f, F) \geq 0$ and $S(k, f, F) \geq 0$ translate into:

$$f \geq \frac{c}{kn_r^i(k)}(q_i^2(k, f) - q_i^2(0)) - \frac{\alpha_a K}{k}\left(1 - \frac{n_r^i(0)}{n_r^i(k)}\right) \tag{A3.35}$$

$$F \leq \frac{c}{kn_r^i(k)}(q_j^2(0) - q_j^2(k, F)) - \frac{\alpha_a K}{k}\left(1 - \frac{n_r^i(0)}{n_r^i(k)}\right) + \alpha_a \tag{A3.36}$$

To prove Lemma 1, we note that $f = F = -\alpha_a$ is in the feasible set: First, it obviously meets the condition that the go-between makes nonnegative profits. Second, relation (A3.33) shows we have $q_i(k, f) < q^*$. Developing the demand function (A3.32) when k is small results in condition (A3.35) being met. Finally, We carry out similar calculations to show that A3.36 holds.

Unfortunately, $n_r^i(k)$ depends on both f and F through $q_j(k, f)$ and $q_j(k, F)$. This means that when platforms rationally anticipate the impact of the fees applied to the competitor on its quality, the feasibility set $\mathscr{F}$ does not have an easy formulation. In order to have a simple formulation of the feasible set $\mathscr{F}$, we slightly relax the assumption of perfect information in Lemma 2.

Lemma 2 (Partial information): In practice, platforms see only the fees they are offered, but not the fees faced by their competitor. Assume that i and j form belief about the fee faced by the other platform, respectively F_e and f_e. Platforms accept to publish and promote, respectively, if fees f and F are such that $P(k, f, F_e) \geq 0$ and

$S(k, f_e, F) \geq 0$. This translates into:

$$f \geq \underline{f} \equiv \frac{c}{kn_r^i(k)}(q_i^2(k,f) - q_i^2(0)) - \frac{\alpha_a K}{k}\left(1 - \frac{n_r^i(0)}{n_r^i(k,f,F_e)}\right) \tag{A3.37}$$

$$F \leq \bar{F} \equiv \frac{c}{kn_r^i(k)}(q_j^2(0) - q_j^2(k,F)) - \frac{\alpha_a K}{k}\left(1 - \frac{n_r^i(0)}{n_r^i(k,f_e,F)}\right) + \alpha_a \tag{A3.38}$$

The feasible set $\mathscr{F}$ is the set of all fees such that $F \leq \bar{F}$, $f \geq \underline{f}$ and $f \leq F$. Numerical applications show that this set is non empty for all expected fees smaller than α_a. In particular this is true when platforms make rational expectations about the fees set by a profit-maximizing go-between.

If firms are naive, and assume user choice and equilibrium quality are unaffected by references, (A3.35) and (A3.36) show that the feasible set is a triangle with $\underline{f} = 0$ and $\bar{F} = \alpha_a$. If firms foresee the change in users' choice but neglect the quality effect, (A3.35) and (A3.36) show that the feasible set has same size as the naive one, but $\underline{f}$ and $\bar{F}$ are both shifted to the left. This is due to the fact references allow i to capture more anchored users, at the expense of j.

B.4 Proof of Proposition 3.4

We seek to analyze relation (3.14) in the case of general cost functions $C(q)$. We have that $\Delta U_r^i(x, 0) = 0$. We now look at positive deviations of k above 0:

$$\frac{\partial \Delta U_r^i(x,k)}{\partial k} = K\frac{\partial q_i}{\partial k} + q_i + k\frac{\partial q_i}{\partial k} - t_r(1-x) \tag{A3.39}$$

From (A3.26), we have that $q_i = (C')^{-1}\left(\frac{\alpha_a K - k(\alpha_a - (f+F))}{2t_r}\right)$. $C'(q)$ is increasing in q, hence so is its inverse function. Hence if $\alpha_a > (f + F)$ the first term and two last terms in (A3.39) are negative. This means only the "diversity" effect is positive, while the quality effect is always negative. Using the implicit function theorem in (A3.26), we derive that

$$\frac{\partial q_i}{\partial k} = -\frac{\alpha_a - (f+F)}{2t_r \frac{\partial^2 C}{\partial q^2}(q)} = -\frac{\frac{\partial C}{\partial q}(q^*)}{\frac{\partial^2 C}{\partial q^2}(q)} \frac{\alpha_a - (f+F)}{K\alpha_a}$$

Hence, these remarks result in:

$$\frac{\partial \Delta U_r^i(x,k)}{\partial k} = q_i - \frac{C'(q^*)}{C''(q_i)} \frac{\alpha_a - (f+F)}{\alpha_a}(1 + k/K) - t_r(1-x) \tag{A3.40}$$

The convexity of the cost function ensures that $\frac{C'(q^*)}{C''(q^*)} > 0$. When $u \equiv f+F$ is arbitrarily close to α_a, Assumption A1 ensures that references are always surplus maximizing: $\frac{\partial \Delta U_r^i(x,k)}{\partial k} > 0$. Indeed, quality is restored to or above the no-reference level (see equation 3.11), and users enjoy more diversity of content.

Conversely, when $u = f + F = 0$, a sufficient condition for references to decrease user surplus when k is small is that $C''(q^*) < \frac{C'(q^*)}{q^*}$ (i.e. the cost function is not too convex[26]). This condition is met if $C'(0) \geq 0$ and $C'''(q) < 0$.

To sum up, when costs are not too convex and denoting $u = f + F$ and $g(u) \equiv \frac{\partial \Delta U_r^i(x,k,u)}{\partial k}$, we have shown that $g(0) < 0$, $g(\alpha_a) > 0$. $g(u)$ is monotonically increasing in u. Hence, by the intermediate value theorem, we have proved that there exists a unique $u^* \in (0, \alpha_a)$ such that references increase user-surplus if and only if $u > u^*$. Simple calculations show that $C(q) = cq^2$ translates into $u^* = \frac{4ct_r^2+\alpha_a k}{K+k}$. This proves Proposition 3.4.

B.5 Proof of Proposition 3.5

We use the expression of profits (3.16) to derive:

$$\frac{\partial \Pi_i}{\partial k} = \frac{1}{2}\left(\frac{\alpha_r}{t_r}(\alpha_a - f - F) + f - F\right) + c\frac{\alpha_a - f - F}{(4ct_r)^2}(\alpha_a(K-k) + k(f+F))$$

For low fees $f = F < \frac{\alpha_a}{2}$ profits always increase with references. It is also easy to show that:

$$\begin{aligned}
\frac{\partial \Pi_i}{\partial F} &= -\frac{k}{2}\left(\frac{\alpha_r}{t_r} + 1 + \frac{\alpha_a(K-k) + k(f+F)}{4ct_r^2}\right) < 0 \\
\frac{\partial \Pi_i}{\partial f} &= -\frac{k}{2}\left(\frac{\alpha_r}{t_r} - 1 + \frac{\alpha_a(K-k) + k(f+F)}{4ct_r^2}\right) < 0\,,
\end{aligned}$$

where the second inequality requires assumption A1 to be verified. Hence low fees increase profits and therefore facilitate entry. The analysis of cross derivatives shows that the positive effect of references on entry is magnified by low fees:

$$\begin{aligned}
\frac{\partial^2 \Pi_i}{\partial F \partial k} &= -\frac{1}{2}\left(\frac{\alpha_r}{t_r} + 1 + \frac{\alpha_a K - 2k(\alpha_a - f - F)}{4ct_r^2}\right) \\
\frac{\partial^2 \Pi_i}{\partial f \partial k} &= -\frac{1}{2}\left(\frac{\alpha_r}{t_r} - 1 + \frac{\alpha_a K - 2k(\alpha_a - f - F)}{4ct_r^2}\right)\,,
\end{aligned}$$

[26] With costs functions of the form $C(q) = cq^\gamma$, this translates into $\gamma \leq 2$.

are both negative for k small enough. The case of general cost functions $C(q)$ follows the same steps. It first notes that $\frac{\partial \Pi_i}{\partial F} = -\frac{k}{2} - C'(q)\frac{\partial q}{\partial F}$. Using the implicit function theorem in (A3.26), it results that this expression is always negative. This means that platforms jointly choose a low sponsor fee, which is constrained by the participation constraint of the go-between: $F = f$. Under this constraint, $\frac{\partial \Pi_i}{\partial f} = -2C'(q)\frac{\partial q}{\partial F}$, which again is negative. Hence, bilateral negotiation between platforms results in setting both the sponsor and publisher fees at the minimum feasible level.

B.6 Exclusive contracts and participation fees

Over the course of 2018, some major press groups (Le Monde, Le Figaro, 20minutes and others) have signed exclusive deals with specific go-betweens. These deals entail not only content recommendation to external sources but also self-promotion. They are inherently different from the base service studied in the main body of the paper. In particular, it is reported that these partnerships entail payment guarantees. Ancillary services such as free analytics of reader traffic can also be seen as a form of lump-sum payment from the go-between to platforms. Hence we now consider the case when sponsoring services are exclusive, and we allow for the go-between to set not only per-click fees f and F (commonly referred to as "usage fees" in the literature on two-sided markets), but also some participation fees p_p and p_s. p_p is the lump-sum payment charged to a publisher who displays sponsored links. p_s is the lump-sum payment charged to potential sponsors. We allow these lump-sum payments to be negative to account for, e.g., the free analytics services that the go-between may provide.

To enter, E must subsidize one group, say the group of sponsors such that they accept to join the platform. For this to happen, he needs to set the entry fee sufficiently low such that they are willing to join, even if it results in them not being matched at all:

$$\overbrace{-p_s^E}^{\text{subsidy to join new entrant}} \leq \overbrace{(\bar{F} - F^I)k - p_s^I}^{\text{surplus made with incumbent}} \tag{A3.41}$$

In the case of strict inequality the entrant attracts all sponsors, $z_s^E = 1$. Platform E will subsequently benefit from the intergroup externality when it courts publishers. The latter rationally expects all sponsors to be enrolled with the entrant, who needs to provide a payment

$$(f^E - \underline{f})k - p_p^E \geq -p_p^I\,, \tag{A3.42}$$

so that publishers join the platform. The entrant can set $F^E = \bar{F}$, as it does not affect the participation of either side – see equations (A3.41) and (A3.42). To prevent entry, the incumbent must choose its pricing such that the profits of the entrant are nonpositive:

$$\Pi^E(f^E, F^E, p_p^E, p_s^E) = p_s^E + p_p^E + (\bar{F} - f^E)k \leq 0 \tag{A3.43}$$

Profit maximization of the entrant results in conditions (A3.41) and (A3.42) being met with equality. Inserting them into (A3.43) yields condition:

$$\Pi^E(f^E, F^E, p_p^E, p_s^E) = \Pi^I(f^I, F^I, p_p^I, p_s^I) + (f^I - \underline{f})k \leq 0 \tag{A3.44}$$

For this condition to allow the incumbent to make strictly positive profits, one would need the fee charged to hosts by the incumbent f^I to be less than $\underline{f}$. However, in that case no platform would be willing to publish external links. Hence (A3.44) cannot be negative without the incument's profits being negative. Similarly to the case with no participation fees, this means that preventing entry deterrence is possible, and requires the incumbent to make no profits. The incumbent optimally sets $f^I = \underline{f}$. Thus, we have that there exist only equilibria that provide efficient matching (all sponsors and publishers are with the same go-between), with a unique active firm making zero profit ($p_p + p_s + (F - f)k = 0$). However, the resulting fees are $f = \underline{f}$ and F may lie anywhere in $[\underline{f}, \bar{F}]$, which does not induce the maximum quality in the long run. The multiplicity of equilibria can be reduced by enforcing that payments be per-interaction only, or allowing for heterogeneity in the trading behavior of agents (see Reisinger (2014)).

C Alternative benchmarks: low cost of a second visit

For formal simplicity and to fix ideas, in the body of the paper we chose to focus on the case when, absent a go-between, R-users would single home. We believe this assumption is realistic in the media sector, where reading a newspaper may require a lot of time, and readers have been shown to be very loyal to only a few sources of information (see Flaxman et al. (2016)). Still, in practice some readers may multi-home. In markets other than media, such as flight search engine, many users may multi-home, owing to the relative user-friendliness of their interfaces, that makes multi-homing almost effortless. Here we consider alternative benchmarks for R-user participation and allow for any nonegative visit cost s. We show that as long as multi-homing is only partial, all qualitative results are maintained.

Assume first that $s \in [0 : \underline{s}]$. In that case we showed in Proposition 3.1 that all

R-users multi-home in the absence of interplatform references. Introducing references has two effects:

- they allow all R-users to save the visit cost s
- they increase equilibrium quality by $k\frac{f+F}{4ct_r}$

Hence, following the introduction of references, user surplus is increased by s, on top on a positive quality effect when reference fees are positive.

When $s \in [\underline{\underline{s}} : \underline{s}]$, R-users multi-home in the absence interplatform references. The introduction of these references has two effects:

- they allow all R-users to save the visit cost s
- they increase equilibrium quality by $\frac{\alpha_a K - k(\alpha_a - f - F)}{4ct_r} - t_r - \frac{s}{k}$

Note that the cost savings on visits are same as when $s \in [0 : \underline{\underline{s}}]$. However too small fees induce a decrease in quality.

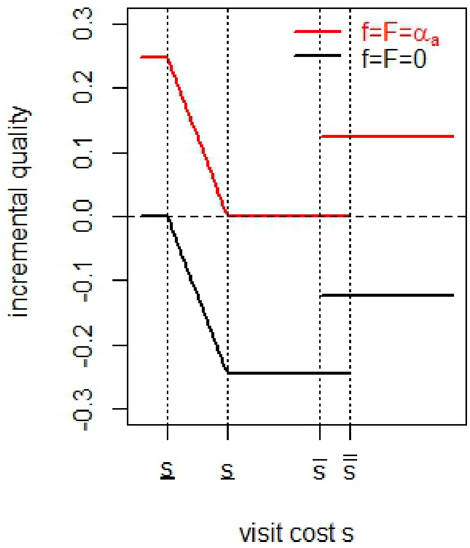
When $s \in [\underline{s} : \bar{s}]$, a measure $m(s)$ of R-users multi-home in the absence of a interplatform references. Hence references have three effects:

- they allow $m(s)$ R-users to save the visit cost s
- they decrease equilibrium quality by $\frac{k(2\alpha_a - f - F)}{4ct_r}$
- they allow $1 - m(s)$ users to view the k items of their platforms of second choice

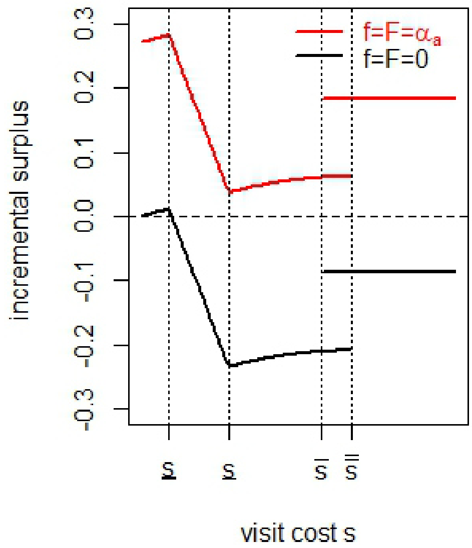
The case in which $s \in [\bar{\bar{s}} : \infty)$ (absent a go-between, all users single-home) is treated in the body of the paper. If $s \in [\bar{s}, \bar{\bar{s}}]$ we showed in Appendix B.1 that there are two pure Nash equilibira. They correspond to the case when $s \in [\underline{s} : \bar{s}]$ and the one covered in the body of the paper, respectively.

Figure 3.17 summarizes graphically the results of Proposition 3.2, 3.4, 3.5 and 3.6, when we allow for any nonnegative visit cost. It is immediate that Propositions 3.3 and 3.7, relative to the strategies of the go-betweens, are maintained.

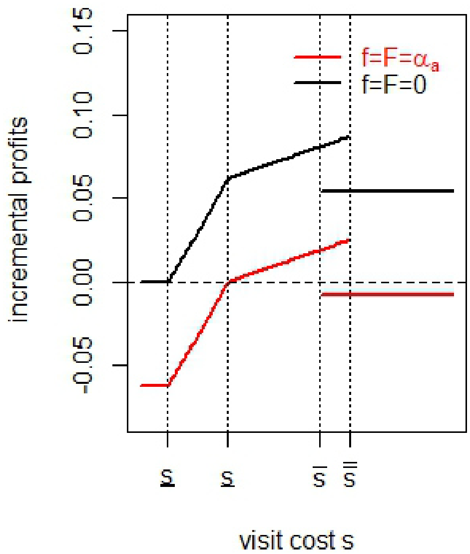
Figure 3.17: Incremental quality, user surplus, platform profit, and social surplus caused by the presence of a go-between, as a function of the visit cost s. Black lines show the case in which there are no fees. Red lines are high fees $f = F = \alpha_a$. $t_r = 1, K = 1, k = 0.1, \alpha_a = 0.5, c = 0.1$



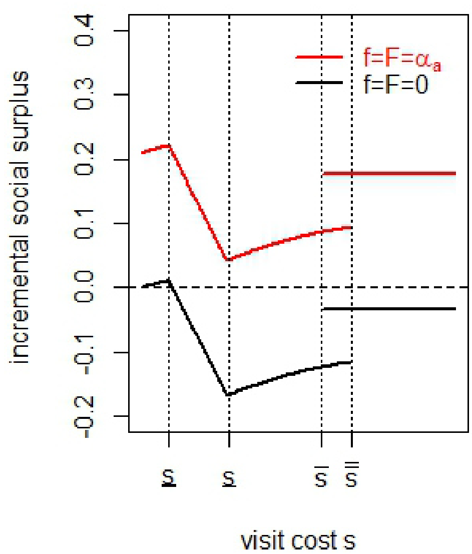
(a) Incremental quality



(b) Incremental user surplus



(c) Incremental platform profits



(d) Incremental social surplus

Chapter 4

The impact of online reputation on ethnic discrimination

About this chapter

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Abstract

We study the impact of reputation on the outcomes of ethnic minority users of a popular ride-sharing platform. Using a large unique dataset, we find that minorities achieve low economic outcomes: compared to non-minority users, their listings are less popular, they sell fewer seats and have lower revenue. We also show that reputation is instrumental in reducing the ethnic performance gap, which is concentrated during the first interactions of minority drivers, and reduces substantially after they establish a reputation. Hence, the reputation system allows minorities to escape the discriminatory treatment over time. To make this point, we develop a model of career concerns, which allows us to model markets' beliefs about the expected quality of service of drivers. We show that these beliefs are formed based on socio-demographic characteristics of drivers and updated with reviews. We claim that a significant part of the initial performance gap is due to erroneous, overly pessimistic beliefs about the expected quality of minority drivers.

Keywords- Discrimination, Sharing economy, Carpooling, reputation systems, Moral hazard, Bayesian updating

1 Introduction

What is the source of online ethnic discrimination? The answer to this question has important implications for our understanding of ethnic inequality in access to online services. Facing this question is as important as ever due to increasing socio-economic differences across ethnic groups and their significant impact on economic growth (see e.g. Alesina et al. (2016)). Discrimination in the offline world has propagated to the online world, and the "collaborative economy" has now embraced the notion of creating trust across social divides,[1] and refers to social capital created with their online reviewing systems as the "cornerstone" of success.[2] This information is critical to online platforms, as these typically match strangers to engage in activity with uncertain outcomes. As documented in the economic literature (see, e.g. Edelman and Luca (2014)), the lack of specific information about other users often leads to reliance on prejudice and ethnic bias. If priors based on ethnicity, gender or race, are not subject to change due to reputation, addressing online discrimination might require drastic changes in the design of

[1] BlaBlaCar claims that their reputation system recreates "a sense of trust almost comparable to the level of trust in friends" (Mazzella and Sundararajan (2016)), and that carpooling makes people "more open to others" (Blablacar (2018)).

[2] TED talk by Joe Gebbia: https://www.youtube.com/watch?v=16cM-RFid9U , last accessed on October 8, 2018.

many popular marketplaces (Edelman et al. (2017)). If, by contrast, online reputation allows minority users to correct market biases and narrow the gap – as we claim in this paper– then improving the efficiency of reviewing systems might constitute an effective means to tackle the issue. Furthermore, if discriminatory treatment can be countered with online reputation, it is essential to understand the tools that minorities can use to their benefits.

This paper empirically tests whether the gap in economic performance across ethnic groups changes with reputation. Using a unique dataset collected with a web-crawler[3] on a popular ride-sharing platform, we find that drivers from ethnic minorities are achieving lower economic outcomes than non-minority users, especially upon entry to the platform. We show that only part of the difference is caused by statistical discrimination, which is a discriminatory treatment due to correct expectations formulated on the basis of observed socio-demographic characteristics. We show that a significant part of the difference in outcomes cannot be justified in terms of statistical discrimination alone, and we attribute the remaining difference to overly pessimistic (erroneous) beliefs about the quality of service provided by minority drivers. Importantly, establishing a reputation updates the beliefs of users and substantially decreases the performance gap.

Our analysis is performed on the popular French carpooling platform BlaBlaCar. Three features of the platform design and usage practice provide us with a unique opportunity to study the ethnic performance gap. First, BlaBlaCar is used by non-professional drivers (in contrast, e.g. to the vast majority of Uber drivers) and does not require significant financial capital (in contrast,e.g. to real estate in the case of Airbnb), which results in a share of ethnic minorities roughly representative of the general composition of French population. Second, the design of the website enables us to study the history of reviews for all drivers that we observe, and the high frequency of usage gives us the possibility to follow the "career" paths of drivers. Third, we observe all drivers available on a given trip, together with their economic outcomes and a detailed description of each listing, which allows us to analyze the performance of individual drivers while controlling for a rich set of observables including the specific characteristics of the drivers, listings and routes.

We first present reduced form evidence of a performance differential between minority and non-minority drivers upon entry to BlaBlaCar. We show that minority users receive 11% lower revenue (where 4.7% is due to lower prices); the gap persist despite controlling for a rich set of variables. We also show that the gap significantly decreases as users collect reviews. We revisit the profiles of drivers a couple of months after the

[3] A web-crawler is a bot that systematically browses and indexes selected webpages.

initial data collection and find no significant differences in exit and inactivity patterns. This information allows us to reject the change in the composition of the population of drivers as an explanation for our results. Reduced form evidence suggests that statistical discrimination, championed in the existing literature on this topic, is most likely not the only factor.

The notion of statistical discrimination refers to the discriminatory treatment of an individual due to her socio-demographic characteristics. However, for such discrimination to be a persistent source of inequality it must be based on true differences in expected quality of service. If the gap in economic outcomes of different socio-demographic groups narrows over time, another mechanism must also play a role. In this paper, we propose the updating of an erroneous prior about the distribution of quality of service of minority drivers as the explanation for the observed market outcomes.

To disentangle statistical discrimination from erroneous beliefs, we develop a structural model of career concerns, inspired by Holmström (1999), whereby users care about the reviews they receive and exert efforts to maximize life-long consumption. This process allows us to explicitly model belief formation and updating. Furthermore, from the market outcomes of minority entrants, we infer the market prior about the true distribution of the quality of minority drivers as well as the impact of reviews on updating of these beliefs. In this framework, we show that part of the gap is due to differences in expected quality, which we relate to statistical discrimination. The remaining part (2-4% of revenue), we attribute to erroneous, overly pessimistic beliefs about the distribution of quality.

The structural model enables us to perform counterfactual analyses. First, we calculate the value of a high grade received at the beginning of a career. We measure the discounted sums of predicted gains in revenue due to such a grade and compare them across drivers. Two key factors determine this value: first, a rating that exceeds expectations impacts positively the belief about the type of a driver – and in turn her expected profits. Second, an additional review reduces uncertainty about the expected true type. These elements combined result in a sizeable (more than four times) difference in the value of a good review across ethnic groups.

In the second counterfactual analysis, we compare market outcomes with and without the reputation system. We disentangle several forces that are at play. First, the reputation system forces drivers to exert effort, which leads to demand expansion. Second, we quantify the total cost of effort provision. Third, we note that undertaking effort allows individual drivers to signal their quality. Comparing across these populations, on average, minority drivers are providing more effort than non-minorities; therefore they bear the higher cost. We find that, despite the higher cost of effort provision, minorities are the populations who benefit the most from the implementation of an efficient reputation system, as they benefit more from the updating of beliefs.

Relation to the literature: This paper relates to several strands of economic literature. First, the economic theory of discrimination, generally, follows two traditions: taste-based discrimination, formalized by Becker (1971), attributes discrimination to a preference against interacting with some economic agents. The theory of statistical discrimination, due to Phelps (1972) and Arrow (1973), explains discrimination in terms of differences in expected productivity across groups. This paper follows the latter.
Second, our focus is on differences in economic outcomes across ethnic divisions. Alesina et al. (2016) documents the extent of ethnic inequality worldwide. A large body of work has sought to analyze the economic consequences of ethnic discrimination. Banerjee and Munshi (2004) quantifies aggregate loss due to discriminatory investment decisions, Hjort (2014) shows the economic costs of ethnic preferences in team production. Discrimination against ethnic minorities in digital markets has been mostly studied in the context of short-term house rentals: Edelman and Luca (2014), Edelman et al. (2017) and Laouenan and Rathelot (2017). Closely related to our empirical analysis, Farajallah et al. (2016)[4] shows that ethnic minority users of a car-pooling platform set lower prices. The relative anonymity of digital markets seem to be an enabler of statistical discrimination, as the vast majority of empirical work suggests that the magnitude of ethnic discrimination online has severe economic consequences. A different result, in the context of gender discrimination, is shown by Cook et al. (2018), who argues that usage patterns can account for most of the gender gap. We contribute to this literature by providing a model of explicit belief formation and updating, which allows us to characterize market beliefs about the quality of service provided by ethnic minorities.
Third, a key result of our paper is that difference in performance across ethnic groups changes when more information about individuals in these groups is acquired. Similar results are obtained by Bartoš et al. (2016), and by Agrawal et al. (2016). Sociological research has also studied the potential of reputation systems to offset trust judgments (e.g., see Abrahao et al. (2017), Tjaden et al. (2018)). We argue that the source of discrimination can be determined by following the performance differential over time; this has been shown before by, e.g., Fang and Moro (2011). The theory of dynamic

[4] Castillo et al. (2013), Goddard et al. (2015), Ge et al. (2016) also study discrimination in transportation systems.

discrimination has been recently formalized by Bohren et al. (2018). We have two main contributions to this literature: we provide a quasi-experiment to show a causal link between the acquisition of information and performance improvement, and we develop a formal model, where we study the impact of the reputation system on ethnic discrimination.

Fourth, our structural model builds on the literature on dynamic moral hazard. We generalize the seminal model of Holmström (1999). Employer learning has been also captured by Chiappori et al. (1999) and Altonji and Pierret (2001).

Finally, recent economic and computer science literature has studied the effectiveness and design of reputation systems, some notable projects including Nosko and Tadelis (2015), Cabral et al. (2010), Bar-Isaac and Tadelis (2008), Liu and Skrzypacz (2014), Livingston (2005), Jolivet et al. (2016), Bolton et al. (2004), Mayzlin et al. (2014), Jullien and Park (2014) and Zervas et al. (2015). These studies focus on understanding how consumers react to the information provided. They aim at improving the accuracy of the reputation system by, for instance, reducing fraud or providing adequate information. Spagnolo (2012) and Butler et al. (2017) use laboratory experiments to show that a reputation system, may hinder the entry of new participants. We show that the accuracy of the reputation system has important implications on the minority performance gap.

The rest of this paper is organized as follows: Section 2 describes the functioning of the carpooling platform we focus on, as well as our data gathering process. Section 3 provides reduced form results documenting an output gap between minority and non-minority drivers, which is followed by a study of the positive effect of reputation building using a cross-section, a panel and a matching method. Section 4 adapts a model of career concerns to our setting and estimates it together with a discrete choice demand model. It shows that minorities disproportionately benefit from an informative reputation system. Section 5 concludes the study.

2 Empirical context and data collection

BlaBlaCar is an online marketplace for ride-sharing that was established in 2006 in France and today operates in 22 countries, mostly in Europe, but also Mexico, India, and Brazil. The platform has eight million active drivers and over 50 million passengers[5], which makes BlaBlaCar the largest ride-sharing platform in Europe. BlaBlaCar enables

[5] www.techcrunch.com/2017/04/10/how-blablacar-faced-growing-pains-and-had-to-change-its-focus

drivers to sell seats in their cars that would otherwise be empty. In the spirit of the sharing economy, BlaBlaCar attempts to limit usage of its platform by "professional" drivers. This restriction is reflected in the pricing rules: drivers receive price recommendations based solely on cost considerations. The suggested price is linear in distance: 0.062 EUR per km. Drivers can deviate from this price, but the price is capped at 0.082 EUR per km. Furthermore, the number of seats users can offer is limited. Having two passengers booked with BlaBlaCar should allow a driver to cover her fuel costs; however, the price cap should prevent drivers from running a profitable business.

A potential passenger looking for a ride between a pair of cities sees a list of all available drivers ranked, by default, by time of departure, together with basic information: a photo of the driver, her name, average rating, a few details about the ride and the price. To obtain more information and, in particular, the history of reviews, a prospective passenger can click and visit the profile of the driver. Examples of profiles and listing pages are provided in Appendix A. The passenger chooses the listing that she finds the most attractive and sends a booking request. The selected driver then decides whether to accept. Roughly half of the drivers choose the automatic acceptance feature while posting a ride. Finally, payment is made upfront via the BlaBlaCar online system. BlaBlaCar fees (see AppendixA) are deducted from the price paid by the passenger.

Passengers and the driver are encouraged to leave a review that consists of a written comment and a number of stars from 1 to 5. The review system has a simultaneous reveal feature, which means that a user cannot observe a received review unless she writes one herself or the time to write one (two weeks) has elapsed. Only after both reviews are sent do they become available to other users.[6]

Data collection: We have collected our dataset using a web-crawler designed by us specifically for the website www.blablacar.fr, from 1.07.2017 to 18.03.2019. The program first randomly selects a route from a list of predefined trips between the largest cities in France. Trips start/end in Paris or its vicinity and have their other end in one of the other 110 largest cities in France. Crawling through the site, the program gathered all the information available to prospective riders, including the price posted by the driver, time and date of the posting and planned departure, destination, origin, type of car, and whether pets or large luggage are allowed. The data also include information related to economic outcomes that the listing has already achieved, that is, the number of clicks it has received (views) and how many seats have already been sold. Clicking on the listing

[6] Over the years, BlaBlaCar has introduced a few changes to their reputation system, which affected grading behavior. Appendix B discusses these changes.

is necessary to book a trip, and clicking opens a detailed description of the ride. After visiting this page, the passenger can still change her mind at no cost. By calculating the product of sold seats and price, we determine revenue collected by drivers at the moment we visit their listings. Next, we open the individual profiles of all drivers available on a given route. For each driver, we observe her name, age, picture, a short biography, number of Facebook friends, etc. Most importantly, we collect the entire history of received ratings and written reviews. An important feature of our data collection process is that we simultaneously observe listings that have been available for different periods of time; in fact, some of the listings could have been posted just before our visit. This explains why many of our observations have zero sold seats and zero revenue. To account for this fact, we control for how long a given listing is available and how many hours are left until departure. Finally, listings that have not sold any seats have zero market shares in our demand estimation presented in the structural model section, which causes technical complications. To account for this factor, we have collected a supplementary, smaller, dataset through BlaBlaCar API, where we observe economic outcomes at the moment of departure – specifically, the number of seats finally sold. We observe that the vast majority of listings sell at least one seat. We therefore use this sample to perform robustness checks.

Additionally, we have matched this data with several other datasets. Gender and ethnicity have been established with two complementary methods. First, we use the ethnic origins of names database published by the French government and supplemented with some other publicly available sources.[7] Translations of names with foreign origins into French show considerable diversity. We phonetically encode our name lists and allow for small spelling mistakes to improve our classification. Second, to increase precision, we also use machine learning software[8] to confirm the matching procedure based on facial recognition. A detailed description of our gender and ethnic identification process is provided in Appendix C where we show that both techniques –name and facial recognition– complement each other. Our definition of minority drivers is based on names with an Arabic or African origin or connotation: in this practice, we follow most of the existing literature. However, by considering both groups and using photo recognition together with name connotation, our approach constitutes an extension of the definition of minorities compared to prior investigations of discrimination on this platform, which restrict the definition of minorities to drivers with an Arabic-sounding name (see Farajallah et

[7] www.data.gouv.fr/fr/datasets/liste-de-prenoms , www.signification-prenom.net, www.madame.lefigaro.fr/prenoms/origine. The complete list of names and origins is available upon request.

[8] www.kairos.com

al (2016)). We proxy the quality of the car by approximating its value with the average price of the same type of car posted on eBay in Germany using data from a Kaggle data science challenge.[9] Fuel costs are potentially significant pricing factors. The fuel efficiency of cars is calculated by matching car names with a dataset of fuel consumption of cars at long distances (French environment and energy management agency – ADEME). We also collect data on city-level daily average fuel prices and highway tolls to construct instruments for prices. Distances and expected time by car or public transportation are calculated using google.maps API. We also include the suggested and maximum prices set by BlaBlaCar. Information specific to the city of destination/departure is included, such as population, median income, and index of crime (French government statistics INSEE). We also have data on strikes related to transportation services (in particular, railways) that occurred in Spring 2018 and created demand shocks. Descriptive statistics of selected variables at the observation level (i.e. ride level) are shown in Table 4.1.

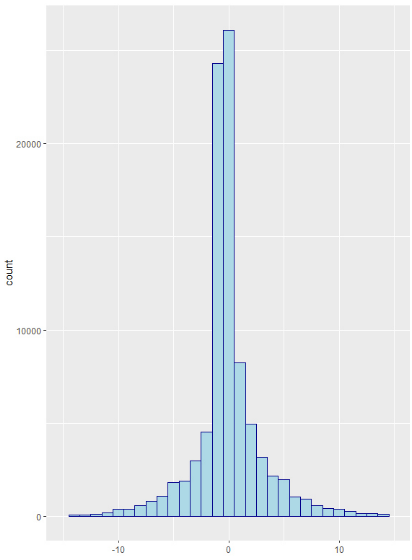
The average price of a ride is 31 euros for a traveling distance of 400 km in a car worth 6000 euros. The average driver is 38 years old and has posted (successfully or not) almost 40 rides in the past. Most of the drivers are men (73%), and approximately 14% of drivers are from a minority. In our dataset, we have approximately 550.0000 observations. Each driver and ride have a unique ID, and given that we observe some drivers multiple times, we can construct a panel dataset. Section 3.2.2 describes in detail how this panel is constructed. Unfortunately, we have a number of missing observations for some variables; therefore, we typically have many fewer observations in the estimated regressions.

Key variables: Drivers' strategic decisions are, foremost, setting a price and the number of seats to offer. They receive a suggested price based on distance, from which they can deviate. However, the maximum rate is bounded. Thus, the decision of drivers is essentially whether, and by how much, to deviate from the suggested price. Figure 4.8a shows the distribution of deviation from the suggested amount. Most drivers do not follow the suggested price, and typically deviations are in the range of 0-10 €. A few drivers set a price below the recommendation. This paper focuses on the impact of ethnic status and reputation on economic outcomes, but other, more standard, factors play important roles in these price differentials. Amongst others, fuel consumption and competition with other drivers and with public transportation have significant impacts.

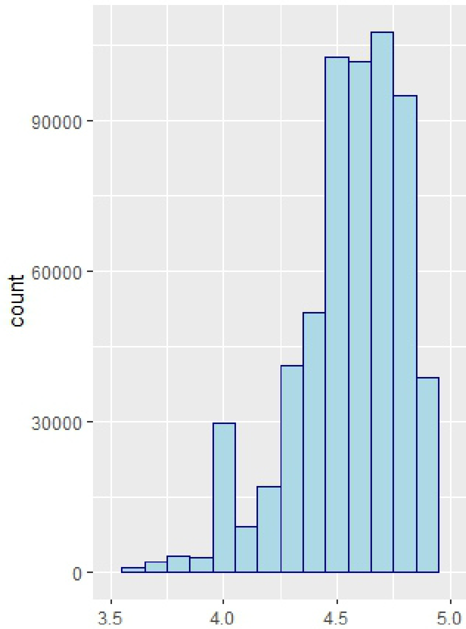
[9]Kaggle is an online community of data scientists and machine learners. Kaggle offers machine learning competitions, for which it makes some data sets available. www.kaggle.com/orgesleka/used-cars-database

Table 4.1: Descriptive statistics.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
price (EUR)	552,518	31.43	15.98	6.00	18.00	41.50	78.50
number of clicks	536,904	16.63	17.57	0.00	3.00	25.00	77.00
sold seats	566,023	0.26	0.58	0.00	0.00	0.00	4.00
revenue (EUR)	559,931	6.42	15.21	0.00	0.00	0.00	82.50
minority	566,023	0.14	0.35	0.00	0.00	0.00	1.00
male	552,530	0.73	0.44	0.00	0.00	1.00	1.00
age (driver)	558,032	37.51	12.80	18.00	27.00	47.00	68.00
reviews (#)	560,331	37.12	60.71	0.00	4.00	42.00	421.00
published rides (total)	537,681	38.84	49.29	0.00	7.00	50.00	256.00
reputation	516,021	4.60	0.31	1.00	4.50	4.80	5.00
seniority (# months)	559,890	44.66	28.03	1.00	23.00	64.00	118.00
posts per month	555,962	1.44	2.17	0.01	0.26	1.62	17.24
picture	566,023	0.97	0.18	0.00	1.00	1.00	1.00
bio (# words)	537,475	7.44	10.38	0.00	2.00	12.00	42.00
car value (,000 EUR)	471,117	6.08	5.04	0.60	3.10	8.06	24.40
fuel consumption	486,604	5.00	0.77	3.65	4.39	5.39	7.50
automatic acceptance	566,023	0.42	0.49	0.00	0.00	1.00	1.00
hours until departure	508,754	95.50	107.47	0.001	20.96	126.47	501.69
posted since	560,361	5.88	7.50	0.00	1.53	6.82	52.56
public transport (travel time)	545,200	3.97	2.42	0.14	2.25	5.41	15.24
length (# km)	550,118	396.34	192.27	67.32	232.00	491.68	906.46
travel cost (fuel & tolls, EUR)	458,018	57.01	29.10	0.00	33.71	72.13	142.14
train strike	566,023	0.04	0.19	0.00	0.00	0.00	1.00
ride description (# words)	509,243	13.49	14.60	2.00	2.00	22.00	93.00
median revenue (city)	532,526	18.98	2.13	13.06	17.76	20.20	30.90
weekday	566,024	0.67	0.47	0	0	1	1
luggage size	116,982	0.89	0.31	0.00	1.00	1.00	1.00
detour	116,454	0.75	0.43	0.00	0.00	1.00	1.00
allows pets	223,774	0.22	0.41	0.00	0.00	0.00	1.00



(a) Price is a strategic variable: distribution of the deviation from the suggested price (excl. commission).



(b) Distribution of reputation.

Figure 4.1: Distibution of price deviations from suggestion (left) and reputation (right)

A characteristic feature of many online reputation systems is that most users leave very good reviews, and as a result, there is little variation in the data (Nosko and Tadelis (2015), Dellarocas and Wood (2008)). This is also the case with BlaBlaCar. Figure 4.8b shows the distribution of the average reputation of drivers. Low ratings are rare, and the vast majority or ratings falls within the 4-5 range (i.e., between “very good” and “perfect”). Finally, we collect several measures of economic outcomes. First, we have the number of clicks a listing has received, which serves as a proxy for the popularity of listings. The number of clicks is a softer measure of demand than sold seats but shows more variation. Second, we observe sold seats, which together with the posted price allows us calculate revenue. Our dataset may miss some very successful rides that are no longer displayed when data are collected, which would lead to bias if the speed at which listings fill differs between minority and non-minority drivers. Since the most attractive listings are more likely to be those of majority drivers (see Appendix F for a discussion of a potential sampling bias), our estimates of the output gap should be seen as a lower bound.

Section 4 examines in detail the fact drivers can exert efforts (strive to be on time, have nice conversations...) in order to get a good review.

3 Reduced form: what is the role of reputation?

We define the performance/output gap as the difference in economic outcomes achieved by minority and non-minority drivers, controlling for all available observables. To provide initial insight into the role played by reputation we present a set of simple reduced form models. A driver's career progresses as she collects reviews. Experienced users provide substantial individual information about the expected quality of service they provide, while expectations about new drivers are based more on socio-demographic information presented on their profiles. There are, necessarily, individual gains to having a good reputation, but as long as initial beliefs about the distribution of quality within a socio-demographic group are correct and the composition does not change over time, there should be no changes in differences in average group performance. If we observe that the difference between groups' average performance differs as drivers' careers progress, either the composition of drivers has changed, for example, due to the exit of less successful drivers, or the initial beliefs about expected quality were incorrect and have been corrected by the reviewing system. We argue for the latter explanation; we will directly check and reject the former. We start by documenting the output gap abstracting from the stage of the driver's career. Doing so, we extend the results of previous literature applied to other online platforms to the case of Blablacar. Later, we contrast the impact of the minority status on drivers who have just entered the platform, as opposed to the minority status on experienced users.

3.1 The output gap

We start by providing a general assessment of the output gap without distinguishing between career stage. This process is similar to that in the studies documenting discrimination in digital marketplaces mentioned earlier. The raw data show that despite setting lower prices (30.1 EUR vs. 31.6 EUR), minority drivers receive fewer clicks (15.4 vs. 16.8), and sell fewer seats (0.258 vs. 0.263) and as a result, have lower revenue (5.81 EUR vs. 6.53 EUR).

We now seek to control for various variables. Throughout the paper subscript i refers to variables related to drivers, while j indicates passenger- or trip- specific elements. Generally, we estimate the following model:

$$y_{it} = \alpha_0 + \alpha_1 X_{it} + \alpha_2 Z_i + c_i + \tau_t + \epsilon_{it}$$

where i denotes an individual driver; t represents her seniority, defined as the number of reviews; y_{it} is the variable of interest (i.e., the number of clicks the listing received, number of seats sold, or revenue generated by the trip); X_{it} is a vector of time-varying explanatory variables (number of reviews, trip-specific attributes); Z_i are time-invariant explanatory variables (gender, minority status); α is the intercept; τ_t is time effects; and ϵ_{it} is an idiosyncratic error term.

Table 4.2 presents estimates of the regressions with various controls, including minority status, on the number of clicks received by listings, sold seats and revenue. It reveals that part of the gap is due to differences in observables.

	Dependent variable:		
	number of clicks	sold seats	revenue
minority	−0.444*** (0.082)	−0.017*** (0.003)	−0.588*** (0.079)
reviews (#)	0.033*** (0.001)	0.002*** (0.0001)	0.041*** (0.001)
reviews sq. (#)	−0.0001*** (0.00000)	−0.00000*** (0.00000)	−0.0001*** (0.00000)
male	−1.400*** (0.064)	0.002 (0.002)	−0.094 (0.061)
age (driver)	−0.058*** (0.002)	−0.001*** (0.0001)	−0.022*** (0.002)
posts per month	−0.557*** (0.020)	−0.010*** (0.001)	−0.201*** (0.019)
bio (# words)	0.001 (0.003)	0.0001 (0.0001)	0.006** (0.003)
car value	0.006 (0.006)	−0.0001 (0.0002)	−0.010* (0.005)
seniority (# months)	−0.017*** (0.001)	−0.0004*** (0.00004)	−0.010*** (0.001)
picture	0.799*** (0.170)	0.001 (0.006)	0.061 (0.163)
automatic acceptance	−0.773*** (0.060)	0.131*** (0.002)	3.135*** (0.057)
hours untill departure	−0.039*** (0.0003)	−0.001*** (0.00001)	−0.021*** (0.0003)
posted since	1.269*** (0.005)	0.011*** (0.0002)	0.292*** (0.004)
public transport (travel time)	1.080*** (0.314)	0.018 (0.011)	−1.519*** (0.299)
length (# km)	0.007*** (0.001)	−0.0002*** (0.0001)	0.013*** (0.001)
night	−0.520*** (0.180)	−0.056*** (0.006)	−1.321*** (0.172)
train strike	4.795*** (0.201)	0.128*** (0.007)	2.949*** (0.191)
ride description (# words)	0.033*** (0.002)	0.001*** (0.0001)	0.021*** (0.002)
weekday	−0.820*** (0.116)	−0.041*** (0.004)	−0.633*** (0.111)
day*weekday	0.724*** (0.137)	0.008* (0.005)	0.001 (0.131)
Constant	13.299*** (0.588)	0.321*** (0.021)	5.671*** (0.560)
Time fixed effects	X	X	X
Trip fixed effects	X	X	X
Observations	302,645	317,643	314,361
R^2	0.247	0.075	0.075
Adjusted R^2	0.247	0.075	0.074
Residual Std. Error	15.174 (df = 302484)	0.560 (df = 317482)	14.819 (df = 314200)
F Statistic	620.566*** (df = 160; 302484)	161.234*** (df = 160; 317482)	158.401*** (df = 160; 314200)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4.2: Output measures regressed over driver and ride characteristics.

First and foremost, minority status has a negative coefficient and is highly statistically significant for all measures of economic performance. Second, reputation, measured by the number of reviews, has a positive impact and is highly statistically significant in all regressions. Finally, several other patterns are consistent across all regressions: younger, female drivers receive better economic outcomes. After we control for the number of reviews, seniority on the platform has a negative coefficient. Drivers with profiles that include extended descriptions and a picture receive higher outcomes.

3.2 The reputation effect

We have shown that, on average, minority drivers receive lower economic outcomes than non-minority driver. In this section, we investigate how this gap differs with reputation. Reputation can be considered from at least two perspectives: quantity of reviews or quality of reviews. Passengers likely consider both dimensions. However, it is a priori not clear how to compare drivers across these two variables (e.g., is a driver with a single 5-star rating better than someone with two 5s and a 4?). Hence, in the reduced form analysis, we focus on the quantity dimension. We integrate both dimensions in the structural model in Section 4.

3.2.1 Cross-section

We divide our sample into three subsamples: listings of drivers with no reputation, i.e., drivers with five or fewer reviews; listings with some reputation (between 6 and 15 reviews); and listings with an established reputation (more than 40 reviews). We estimate standard OLS regressions with the same set of controls as in Table 4.2 for drivers with different levels of experience. The coefficients associated with minority status are presented in Table 4.3; full results are in Appendix F. Minority status has

Table 4.3: Reputation effect, coefficients of minority status

	Dependent variable:		
	revenue		
Reviews:	(0:5)	(6:15)	(40+)
minority	-0.622^{***} (0.142)	-0.450^{**} (0.178)	-0.235 (0.168)
Driver effects	X	X	X
Ride effects	X	X	X
Time effects	X	X	X
Trip effects	X	X	X
Observations	82,563	65,013	68,505
R^2	0.060	0.070	0.096
Residual Std. Error	13.720 (df = 82413)	14.825 (df = 64863)	15.428 (df = 68355)
F Statistic	35.305^{***} (df = 149; 82413)	32.917^{***} (df = 149; 64863)	48.521^{***} (df = 149; 68355)
Note:			*p<0.1; **p<0.05; ***p<0.01

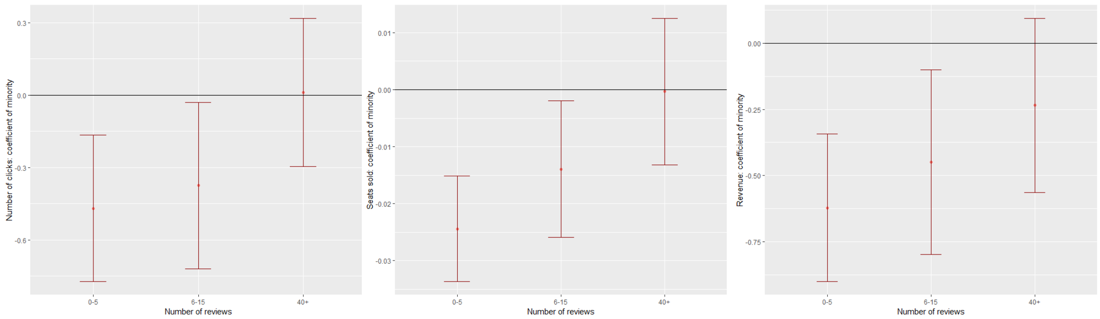


Figure 4.2: Coefficients of minority status at different stages of experience. Dependent variable: number of clicks (left), seats sold (center) and revenue (right)

a significant impact at the beginning of a career. Figure 4.2 illustrates this result for other measures of performance. Minority drivers with few reviews (fewer than 5) receive significantly fewer clicks, sell fewer seats and make less revenue. Crucially, this effect decreases relatively fast and, in some cases, once the reputation is built, is overcome entirely.

Throughout this paper, we define an "entrant" driver as a driver with five or fewer reviews.[10] We observe that the size of the gap decreases as drivers build reputation. Controlling for other observables, the initial gap (drivers with 0 to 5 reviews) is 11.8%. It decreases to 6.9% for more advanced drivers (6 to 15 reviews) and is as low as 1.6% for confirmed drivers (more than 40 reviews). Results are similar with other measures of performance.[11]

3.2.2 Panel data analysis

Thousands of drivers are active on BlaBlaCar at any moment; thus, every time we collect data, we observe only a fraction of all available listings. As a consequence, we see most drivers only once. However, in some cases (22.800 drivers), we see the driver at least twice, which gives us a panel with almost 56.800 observations. However, this sample is unbalanced, with drivers being observed between 2 and 30 times. We use several standard models that allow us to compare the gap associated with being a minority entrant or

[10] Appendix E uses a spell of massive strikes in the French rail transportation sector as exogenous (positive) shocks to the number of reviews received, and justifies that we take this variable as a measure of seniority on the platform.

[11] In terms of the number of clicks, the gap is 2.8% for entrant drivers, 2.2% for advanced drivers, and 0.1% for confirmed. Regarding sold seats, the initial gap is 12.2%. It reduces to 5.5% with five to fifteen reviews and to 0.1% for confirmed drivers. These result are calculated on the basis of the results from cross-section controls, as in Table 4.2.

incumbent entrant. Reduction in the sample size results in lower significance of our estimates. However, the signs and point estimates appear to confirm our hypothesis.

We estimate the following model:

$$y_{it} = \alpha_0 + \alpha_1 X_{it} + \alpha_2 Z_i + c_i + \tau_t + \epsilon_{it}$$

where c_i are individual fixed effects and ϵ_{it} is an idiosyncratic error term.

Here, we report only the variables of main interest; full results are presented in Appendix H.

	Pooled	**Between**	**Random**
Dependent variable:		*number of clicks*	
minority	0.288 (0.202)	0.409 (0.275)	0.317 (0.236)
minority*entrant	−0.678* (0.353)	−0.692 (0.449)	−0.717* (0.387)
Dependent variable:		*sold seats*	
minority	0.002 (0.009)	0.016 (0.011)	0.002 (0.009)
minority*entrant	−0.035** (0.016)	−0.041** (0.018)	−0.035** (0.016)
Dependent variable:		*revenue*	
minority	−0.334 (0.213)	0.022 (0.275)	−0.272 (0.228)
minority*entrant	−0.680* (0.372)	−0.866* (0.448)	−0.741* (0.387)
Observations	56,760	22,794	56,760

Table 4.4: Panel data results, entrant is a driver with less than 15 reviews, full results presented in the Appendix H

We present minority dummies and the products of minority and entrant dummies. Similarly to the cross-sectional analysis in Section 3.2.1, we conclude that upon entering the market, minority drivers receive lower outcomes and that this effect weakens as drivers receive reviews. Again, the reputation effect is significant for all measures of economic performance.

3.3 Alternative explanation: selection

An alternative mechanism that may explain the observed pattern of economic outcomes is the exit of underperforming minority drivers. If after entry minority drivers observe that it is harder for them to sell rides, then their churn rate should also be higher. Alternatively, if they are aware upon entering that they need to collect a few good reviews to achieve higher outcomes, they would not exit, but instead would exert effort to gather good reviews. We provide two complementary sources of evidence showing that a change in the composition of drivers is not the cause of the narrowing output gap. First we note that if minority drivers are facing harder selection, their share in the population of drivers should be a decreasing function of driver seniority.

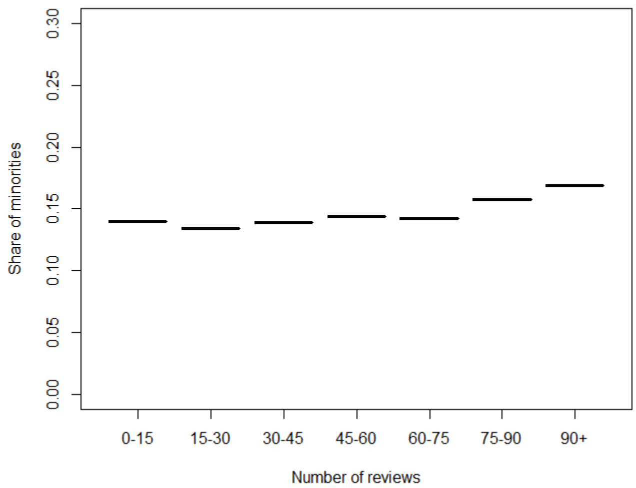


Figure 4.3: Share of minority drivers at different career levels

Figure 4.3 presents the share of minority drivers at different levels of experience, measured by the number of reviews they collected. The share is relatively stable, which suggests that selection cannot explain the reputation effect. This reasoning, however, assumes that entry patterns are constant over time, which is difficult to verify. A second way to look at the problem without relying on this assumption is to revisit the profiles of drivers that we have seen in the past and directly check whether minority drivers are more likely to stop using the platform. In December 2018, we revisited profiles of drivers that appeared in our dataset earlier on and collected newly received reviews. We define two variables to measure the inactivity of drivers *exit*, which takes the value 1 when no extra reviews were received since our last visit and zero otherwise; and the variable *disaffection*, which takes the value 1, when the driver gathered less than five extra reviews. Table 4.5 shows the results of the estimation of a logistic regression with *exit* (column 1) and *disaffection* (column 2) as dependent variables, regressed on various covariates: new drivers are, generally, more likely to leave the platform, while minorities are, in fact, more likely to continue using it. We find no evidence that minority entrants are more likely to leave the platform than non-minority entrants.[12]

Table 4.5: Exit variables, regressed over driver and ride characteristics

	Dependent variable:	
	exit	disaffection
minority	−0.129*** (0.028)	−0.097*** (0.030)
entrant	1.350*** (0.024)	1.419*** (0.025)
minority*entrant	0.079 (0.065)	0.065 (0.066)
age	−0.005*** (0.001)	−0.003*** (0.001)
male	−0.098*** (0.018)	−0.084*** (0.019)
seniority (# months)	−0.005*** (0.0003)	−0.005*** (0.0004)
posts per month	−0.731*** (0.010)	−0.736*** (0.011)
bio (# words)	−0.007*** (0.001)	−0.007*** (0.001)
car value	−0.00000 (0.00000)	−0.00000 (0.00000)
Constant	−0.867*** (0.053)	−1.377*** (0.058)
Observations	160,923	160,923
Log Likelihood	−49,342.620	−44,702.880
Akaike Inf. Crit.	98,779.230	89,499.760
Note:		*p<0.1; **p<0.05; ***p<0.01

These two arguments lead us to the conclusion that the results shown earlier are not due to a change in the composition of drivers but to the causal impact of reputation building.

4 Structural model: the driver's Incentives Problem

The reduced form results show that the outputs achieved by drivers from ethnic minorities are lower than those of non-minority users. Whereas a sizable initial gap in performance exists, it narrows down as reputation is built. This result suggests that the reputation system is crucial for drivers to signal their quality and for passengers to update their beliefs. However, the reduced form results do not allow us to separate differences in the intrinsic quality of drivers from the efforts they actively take; thus, we are not able to observe potential differences in the quality of service provided by minority drivers due to some form of selection on entry or difference in preferences. In this section, we adapt the canonical model of career concerns of Holmström (1999) using ratings as performance measures. Our goal is to decompose the amount of quality of service due to efforts taken by drivers from their intrinsic quality, in order to construct counterfactuals. Efforts, which is sometimes referred to as "labor" in the literature, could take the form of making sure one is on time at the meeting, friendly, drives smoothly, etc.

[12]The same analysis with the number of listings published as a proxy for activity on the platform, instead of number of reviews collected, gives similar results.

First, we focus on the demand side. We estimate a discrete choice model, where beliefs about drivers quality are obtained using a machine learning algorithm that takes drivers characteristics, and already obtained reviews to predicts the next grade. This allows us to describe drivers' incentives to improve the beliefs or the market regarding the service they offer. Second, we discuss the supply side of the market. We present the problem faced by a driver and derive her optimal effort schedule. Using reviews obtained by all drivers, the information available on their profiles, and the characteristics of demand, we derive time preferences and costs of effort provision of drivers. Finally, we compare the outcomes obtained by minority drivers with that of non-minority drivers in counterfactual situations.

4.1 Demand side

Our data set is constructed by conducting a search for a given route and observing all the available listings; thus, we observe the entire choice set available to passengers, together with the output measures for all drivers. Therefore, we can calculate market shares, which we use to estimate a logit demand system with imperfectly informed consumers. We define a market as a route (directed city pair) and a day, which gives us many markets (more than 40.000). Passenger j receives utility from choosing driver i at time t, given by:

$$u_{ijt} = \alpha w_{ijt} + \beta \mathbf{X}_{it} + \gamma p_{it} + \xi_i + \phi_t + \epsilon_{ijt} \tag{4.1}$$

where w_{ijt} is our measure of the quality of driver i, as expected by passenger j at time t. $\mathbf{X}_{it}$ is a vector of covariates, ξ_i are driver characteristics unobserved by the econometrician, and p_{it} is the price of the ride posted by driver i. The error term is assumed to be iid extreme value of type 1. In this simple model, we assume that all passengers have the same valuations for characteristics and prices. The mean utility is denoted by:

$$\delta_{j,t} = \alpha w_{ijt} + \beta \mathbf{X}_{it} + \gamma p_{it} + \xi_i + \phi_t$$

Following Berry (1994), we can equate δ_{jt} with $log(\frac{s_{it}}{\underline{s}_{it}})$, where s_{it} is the market share of driver i in the market in which she operates. We define the market share as $\frac{q_{it}}{M_{it}}$, where q_{it} is the number of seats driver i sold in period t on a given route, and M_{it} is the number of potential buyers in the market where driver i is active at time t. As a proxy for market size M_{it}, we use the maximum number of seats ever sold on the route on a single day. The term $\underline{s}_{it} \equiv \left(1 - \sum_{l \in M_{it}} s_{lt}\right)$ is the share of consumers choosing the "outside option" of not traveling on a given day with any of the drivers.[13]

According to a classical result of the logit model, driver i obtains the following market share:

$$s_{it}(p) = \frac{\exp(\alpha w_{it} + \beta \mathbf{X}_{it} - \gamma p_{it} + \xi_i)}{1 + \sum_{l=1}^{N} (\exp(\alpha w_{lt} + \beta \mathbf{X}_{lt} - \gamma p_{lt} + \xi_l)} \tag{4.2}$$

To estimate the characteristics of demand, we need an accurate prediction of the expected quality of the next ride. Appendix D carries out a textual analysis of the written comments. It shows that the grades already received are a good measure of the satisfaction of passengers of previous rides, as reported in their comments. We conclude that grades are a satisfactory measure of the quality of the ride, as experienced by previous passengers. Taking stock of this observation, we now need to recover the beliefs of passengers regarding the quality that will be offered in the next ride (i.e., the expected grade). At this stage we don't want to impose any functional form on this prediction, which will be based on driver-specific characteristics and all past ratings. We try several machine learning algorithms. Finally, we use Gradient Boosting Machine, which is the technique that performed best. We name the expected grade the "posterior", which will serve as our measure of expected quality. Figure 4.4 presents the distribution of the posterior.

[13] There are many small markets in our dataset; we have approximately 40000 markets, with sometimes fewer than 5 drivers per market. Moreover, we have many drivers who have not sold any of their offered seats at the time of observation; hence, we observe a large number of zero market shares. As noted by Gandhi et al. (2013), a typical "fix" in such a case is to add a small ϵ to all market shares or drop observations with zero market share, which effectively lumps them with the outside option. Unfortunately, both methods lead to biased estimates. In the present report, we add ϵ to the market shares of all drivers and acknowledge the problem. We are working on solving this problem with a subsample of rides observed after completion.

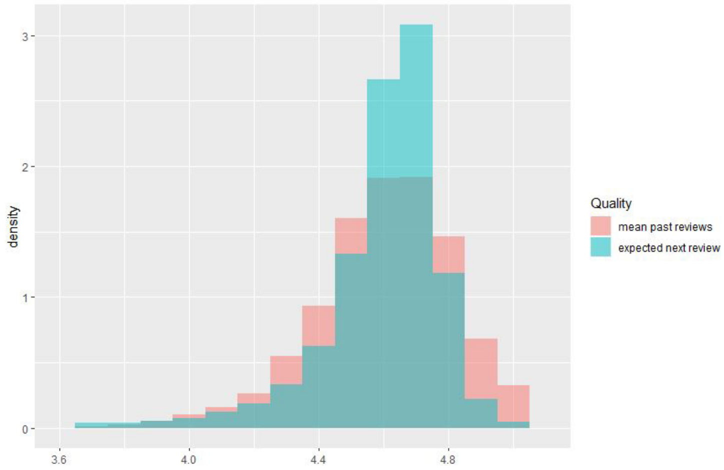


Figure 4.4: Histogram of posterior belief about driver's quality, estimated using Gradient Boosting Machine (blue bars). Red bars are the mean of past reviews.

To address the standard problem of the endogeneity of prices, we employ two instrumental strategies. First, we use cost-shifters: over time, the price of gas changes, and we can observe the average price at gas stations in any given city on any given day.[14] These prices change over time (because of oil price fluctuations) and location (e.g., due to varying intensities of competition between filling stations). Additionally, the level of highway tolls varies across routes. Second, we observe the characteristics of all drivers available in a given market: we derive measures of isolation in the spirit of Berry (1994) or the BLP model (Berry et al. 1995).

A direct consequence of our data collection method is that markets in our main data set have not cleared yet: our crawler replicates the behavior of a prospective passenger, looking for a ride in the near future. This may bias our elasticity estimates downward. To remedy that, we use the second data set described earlier, which consists in re-visiting the rides after their completion. This allows us to observe the realized market share of each driver.

We present our results in Table 4.6, with mean utility as a dependent variable. Column (1) is an OLS regression with the quality measure discussed earlier. Column (2) instruments prices with BLP instruments and column (3) uses cost shifters. Using the specification of the last model (price instrumented with cost shifters), we report the elasticity of demand with respect to various covariates, with bootstrapping (1000 samples) in Figure 4.5. We note that demand is relatively elastic to price (-0.5) and quality (0.6), and relatively inelastic to other covariates.

[14] www.prix-carburants.gouv.fr

Table 4.6: Logit demand

	Dependent variable:		
	mean utility		
	OLS	*instrumental variable*	
	(1)	(2)	(3)
price	−0.030*** (0.001)	−0.022*** (0.003)	−0.013*** (0.004)
posterior	0.105*** (0.028)	0.110*** (0.028)	0.115*** (0.028)
train strike	0.142*** (0.038)	0.143*** (0.038)	0.144*** (0.039)
# drivers in market	0.001*** (0.0002)	0.001*** (0.0002)	0.001*** (0.0002)
talkative	0.004 (0.013)	0.005 (0.013)	0.005 (0.013)
# reviews	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)
weekday	−0.170*** (0.013)	−0.170*** (0.013)	−0.171*** (0.013)
driver age	−0.002*** (0.0004)	−0.002*** (0.0004)	−0.002*** (0.0004)
bio (# words)	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)
automatic confirm	0.265*** (0.013)	0.286*** (0.014)	0.307*** (0.016)
Constant	−1.807*** (0.284)	−2.979*** (0.434)	−4.173*** (0.626)
Observations	48,901	48,901	48,901
R^2	0.396	0.395	0.393
Adjusted R^2	0.394	0.393	0.391
Residual Std. Error (df = 48758)	1.212	1.212	1.214
F Statistic	224.720*** (df = 142; 48758)		
Note:			*p<0.1; **p<0.05; ***p<0.01

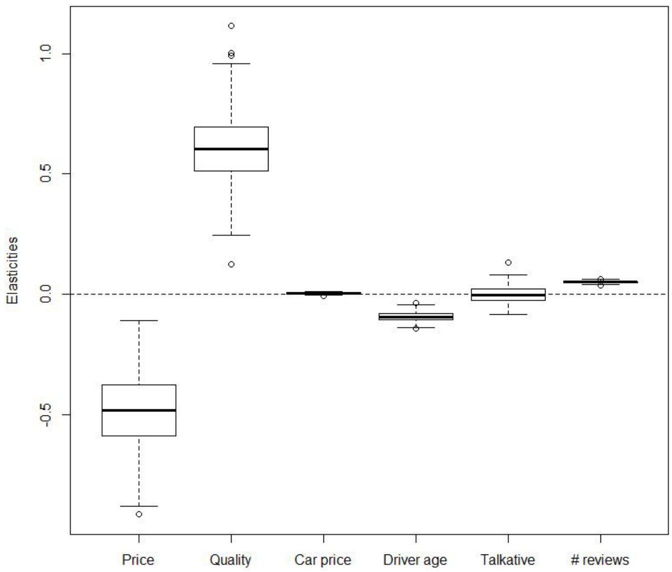


Figure 4.5: Estimation of demand elasticity with respect to price, expected quality, car price, driver age, how talkative the driver is, and number of reviews. Price instrumented with cost-shifters, data after completion of rides.

4.2 Supply side

To model the problem faced by drivers we adapt a canonical model of career concerns by Holmström (1999). This is a dynamic game of incomplete information. Let η_i be a measure of the driver's talent. Suppose that talent is fixed and incompletely known both to the market and to the driver herself. However, some characteristics of the driver (gender, age, ethnicity, etc.) are publicly observed. A combination of these characteristics is indexed by I and denotes the population to which a driver belongs (for example the population of young, female, non-minority drivers). The market (here, the passengers) has an initial belief about the intrinsic quality of driver i from population I because the distribution of types in the population is known. We assume that the quality in population I is distributed normally with mean m_I and precision (inverse of variance) h_I: $\eta_i \sim N(m_I, h_I)$. The output of driver i from population I in period t is given by:

$$y_{iIt} = \eta_i + a_{it} + \epsilon_{it}, \ t = 1, 2, ...$$

where $a_{it} \in [0, \infty]$ is a measure of exerted effort (input of labor), and ϵ_{it} is a stochastic noise term, which is assumed to be independent from types and efforts and distributed normally with mean zero and precision h_ϵ. Exerting effort a_{it} induces a non-decreasing, convex cost $g(a_{it})$. Drivers maximize the discounted sum of profits. The market will learn about the driver's type by observing the reviews left by the previous passengers, which we assume are unbiased measures of quality. Denote a_i^{t-1} the history of efforts of driver i until $t-1$. $\pi_{it}(a_i^{t-1}, p_{it})$ is the expected revenue of that driver. She solves the following problem:

$$\max_{p_{it}, a_{it}} \mathbf{E} \left\{ \sum_{t=1}^{\infty} \beta^{t-1} \left[\pi_{it}(a_i^{t-1}, p_{it}) - g(a_{it}) \right] \right\} \tag{4.3}$$

We need to characterize the optimal path of efforts. Two key elements of the Holmström (1999) model are still in place:

- effort is non-contractible; therefore, only reputation considerations can shape the level of effort
- with correctly specified prior and symmetric incomplete information, market anticipates the correct level of effort; thus the learning process about the driver's type is the same as in Holmström (1999)

The per-period revenue of driver i competing against N drivers writes:

$$\pi_{it}(a_i^{t-1}, p_{it}) = M_{it} s_{it} p_{it} \tag{4.4}$$

where M_{it} is the size of the market where driver i operates in period t and s_{it} is defined in Equation (4.2). Similarly to Holmström (1999) the optimal effort supply a_{it}^* has to satisfy:[15]

$$\sum_{s=1}^{+\infty} \beta^{s-t} \cdot \mathbf{E}\left[\frac{\partial \pi_{is}}{\partial a_{it}^*}\right] - g'(a_{it}^*) = 0 \tag{4.5}$$

The following proposition generalizes the Holmstrom model to the case when drivers face elastic demand.

Proposition 4.1. *The equilibrium sequence of effort goes asymptotically towards zero as driver gain experience :* $\lim_{t\to+\infty} a_{it}^* = 0$*. Keeping driver's expectations about future seats sold constant over time, effort is a strictly declining sequence.*

Proof. To find the optimal effort schedule, we first note that efforts exerted at period t does not influence profits in period t, nor previous periods. It does affect future profits, starting from $t+1$. Profit-maximizing drivers will chose efforts at time t such that the marginal cost of efforts equates anticipated marginal revenues, and relation (4.5) simplifies to:

$$g'(a_{it}^*) = \sum_{k=t+1}^{\infty} \beta^{k-t} \mathbf{E}\left[\frac{\partial \pi_{ik}}{\partial a_{it}}\right] \tag{4.6}$$

First, we calculate the derivative of per-period profits (equation 4.4) at $k > t$ with respect to effort at t:

$$\begin{aligned}\frac{\partial \pi_{ik}}{\partial a_{it}} =& M_k \cdot \left(\left(\frac{\partial S_{ik}}{\partial w_{ik}}\frac{\partial w_{ik}}{\partial a_{it}} + \frac{\partial S_{ik}}{\partial p_{ik}}\frac{\partial p_{ik}}{\partial w_{ik}}\frac{\partial w_{ik}}{\partial a_{i,t}}\right) p_{ik}^* + \frac{\partial p_{ik}}{\partial w_{ik}}\frac{\partial w_{ik}}{\partial a_{i,t}} S_{it}\right) \\ =& M_k \frac{\partial S_{ik}}{\partial w_{ik}}\frac{\partial w_{ik}}{\partial a_{it}} p_{ik}^* \end{aligned} \tag{4.7}$$

, where the second equality stems from driver's price optimization. From the expression

[15] We use the dominated convergence theorem to interchange the derivative with the expectation

of the market share in equation (4.2) we derive easily the following relations:

$$\frac{\partial s_{ik}}{\partial w_{ik}} = \alpha s_{ik}(1 - s_{ik}) \tag{4.8}$$

$$\frac{\partial s_{ik}}{\partial p_{ik}} = -\gamma s_{ik}(1 - s_{ik}) \tag{4.9}$$

We assume the driver sets its price optimally at each period. Profit maximization easily translates into:

$$p^*_{ik} = \frac{1}{\gamma s_{ik}} \tag{4.10}$$

$$\frac{\partial p^*_{ik}}{\partial w_{ik}} = \frac{\alpha s_{ik}}{\gamma(1 - s_{ik})} \tag{4.11}$$

Finally, we observe that the marginal effect of effort on perceived output is the same as in Holmström (1999). For $k > t$:

$$\frac{\partial w_{ik}}{\partial a_{it}} = \frac{\partial}{\partial a_t} \left\{ \frac{h_I m_I}{h_{Ik}} + \frac{h_\epsilon}{h_{Ik}} \sum_{s=1}^{k-1} \left(m_I + a_s - \mathbf{E}\left[a^*_{is}(y^{s-1})\right] + \mathbf{E}\left[a^*_k(y^{k-1})\right] \right) \right\} = \frac{h_\epsilon}{h_{Ik}} \tag{4.12}$$

where $h_{Ik} = h_I + (k-1)h_\epsilon$. Inserting results (4.8) to (4.12) into (4.7), we obtain:

$$\frac{\partial \mathbb{E}(\pi_{i,k})}{\partial a_{i,t}} = \frac{h_\epsilon}{h_{Ik}} \frac{\alpha}{\gamma} \mathbb{E}[M_k s_{ik}] \tag{4.13}$$

All terms of this expression are bounded. Further, we observe that $\sum_{s=0}^{n} \beta^s$ is a converging sequence when $|\beta| < 1$. Hence, it is a classical result that $\sum_{s=t}^{+\infty} \beta^s$ converges to 0 as t goes to infinity. From this, we derive the first part of the proposition and:

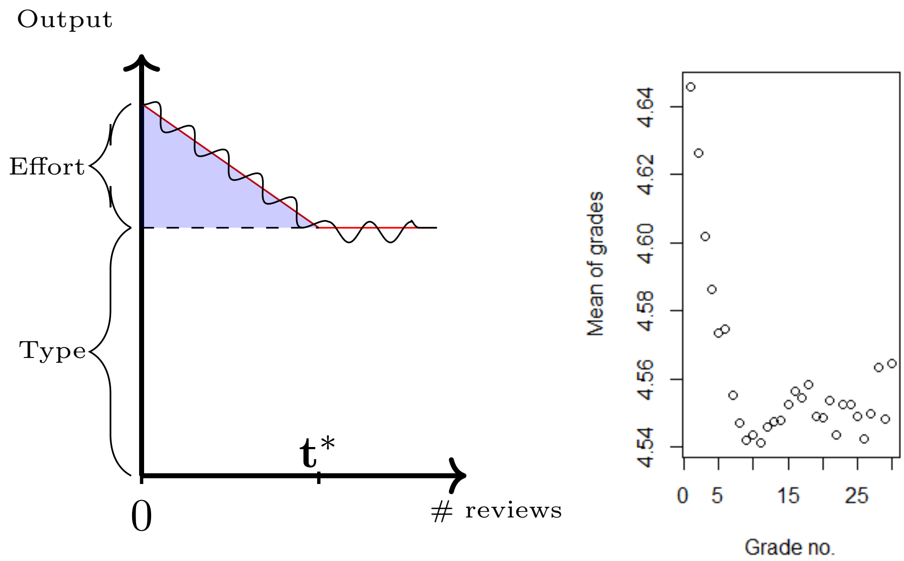
$$g'(a^*_{it}) = \frac{\alpha h_\epsilon}{\gamma} \sum_{k=t+1}^{\infty} \beta^{k-t} \mathbf{E}\left[\frac{\mathbb{E}[M_k s_{ik}]}{h_{Ik}}\right] \tag{4.14}$$

We finally observe that, when $\forall k \in \mathbb{N}, \mathbf{E}\left[M_{ik} s_{ik}\right] = Q_i$:

$$g'(a^*_{it+1}) - g'(a^*_{it}) = Q_i \frac{\alpha h_\epsilon}{\gamma} \sum_{k=1}^{+\infty} \beta^k \left(\frac{1}{h_{t+k+1}} - \frac{1}{h_{t+k}} \right) < 0 \tag{4.15}$$

which completes the proof. □

The evolution of drivers output as predicted by this adaptation of the Holmstrom model is illustrated in Figure 4.6a; to be compared with the actual data in Figure 4.6b



(a) (b)

Figure 4.6: Illustrative prediction (left) and actual average grade (right) at different career stages

Description of the data and recovering parameters of the model: Data from the reputation system is characterized by high frequency of performance reports, which allows for a precise study of effort dynamics. For all 550.000 drivers in our dataset, we have a full history of ratings obtained from their first ride until the moment we collected the observation. Hence, we can study the changes in ratings received depending on the level of experience. After restricting the sample to only drivers who have at least 30 reviews (so that we see all drivers in each stage of their career), we are left with 1.5 mln observations. Figure 4.6 (right panel) shows the average ratings at different stages of the drivers' careers. The first point on the left graph is the average first rating. We see that the ratings are high at the beginning and stabilize at a certain level as more ratings are collected.

Following the logic of the theoretical model presented previously, we recover the parameters in the following way:

- The intrinsic quality (type η_i) of an individual driver is the average of her ratings after they stabilize (in practice, after the 15th rating).

- The distribution of the error term is normal with mean zero, and the variance is given by the total variance of the ratings after they have stabilized.
- The effort of an individual driver during their $t-th$ ride is the difference between the $t-th$ rating received and her type.

In our approach, 15 reviews are sufficient for the market to deduce the true type of any driver. Before 15 reviews are collected, passengers must form expectations of quality based on the publicly available information. When looking at a driver with no reviews, a passenger will judge her quality as the mean quality of the population of that driver. In subsequent interactions, passengers will also take into account the reviews she received.

We estimate Equation (4.6) with quadratic costs of efforts $g(a_{it}) = A_1 a_{it} + A_2 a_{it}^2$ by non-linear least squares. Table 4.7 displays our parameter estimates.

	A_1	A_2	β
Coef.	2.14	18.08	0.94
Std. error	0.87	2.70	0.02
t-stat.	2.47	6.71	48.36
p	0.01	0.00	0.00

Table 4.7: Estimation of the supply model with quadratic costs of effort

4.3 Counterfactual analysis

The characteristics of demand, most importantly demand elasticity to price and quality, have been estimated in Section 4.1. The characteristics of the supply side, such as driver's discount factor and the structure of the costs of efforts were estimated in Section 4.2. We are now equipped to run counterfactual analyses.

The patterns of performance and reduced form regressions suggest that our measure of expected quality should explain the persistent part of the minority gap, which may be due to factual differences in quality, as measured by reviews. Assuming passengers form rational expectations, controlling for expected quality should provide results that are on average correct. We observe, however, that our measure of expected quality cannot account for the part of the gap that narrows down over time. In other words, our data shows that minority drivers underperform compared to their (rationally) expected quality at the beginning of their career.

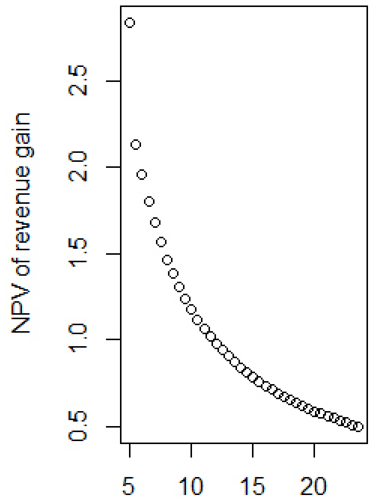
If we attribute all of the remaining gap (the gap that remains unexplained by expected quality) to erroneous beliefs about the average quality of a population, we can recover the market's belief about the initial distribution of perceived types in the population of minorities. The intrinsic quality in the population of minority drivers has a mean of 4.46 and is distributed between 4.41 and 4.75, whereas the quality distribution that would justify the gap in market shares is distributed between 4.08 and 4.42, with a mean of 4.12. Given the high concentration of types in our sample, these values represent a large difference.

First counterfactual: value of a high rating. In previous sections we stressed the importance of the first few interactions for drivers to reveal their type. This effect is especially strong for minorities, to whom reviews give the opportunity to update the beliefs of passengers that may be biased against them.

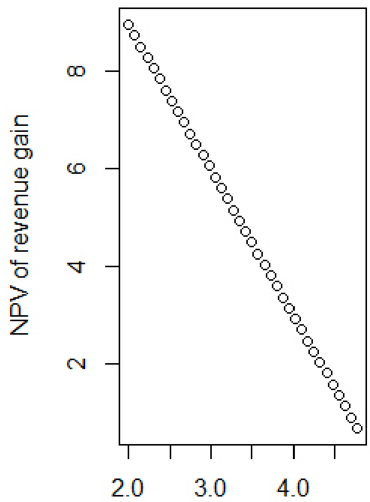
We now calculate the value that different drivers derive from a good review. Equation 4.16 describes predicted quality.

$$w_{iIt}(y^{t-1}) = \frac{h_I m_I}{h_I + t h_\epsilon} + \frac{h_\epsilon}{h_I + t h_\epsilon} \sum_{s=1}^{t} \left(y_{iIs} - a^*_{iIs}(y^{s-1})\right) + a^*_{iIt}(y^{t-1}) \tag{4.16}$$

It shows that a good review obtained at the initial period $t = 1$ (i.e., a passenger reports a high output y_{iI1}) will have a different impact on drivers depending on the level of uncertainty about their type (measured by h_I) and the expected rating (m_I). Suppose that a driver receives a 5-star review instead of the first rating that would be expected to get on the basis of the observables of her population. Figure 4.7 provides some comparative statistics.



(a) Revenue gains as a function of the precision of the population h_I



(b) Revenue gains as a function of the expected mean of the population m_I.

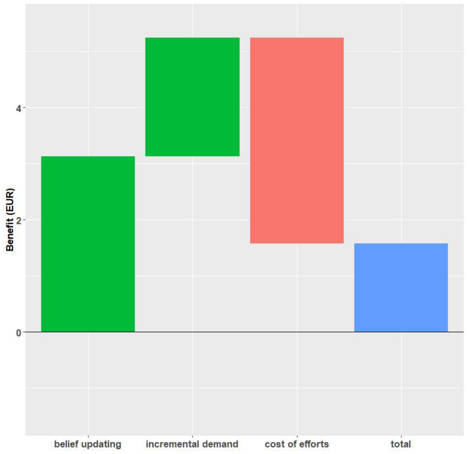
Figure 4.7: Revenue gains from a 5-star rating

Both panels present the discounted sum of gains in revenue due to a 5-star review. Panel (a) fixes the expected rating (at 4.74, which is the average expected rating) and varies the level of precision (h_I) of types in a populations. We see that drivers from a population with very heterogeneous members (low h_I) derive high gains from a good review. Panel (b) fixes the population precision at the average level and varies the expected rating, based on a driver's population. We observe that a driver whose expected rating is the lowest exceeds expectations the most and derives the highest gains from a good rating, whereas a driver with an expected rating of 5 simply meets the expectations of passengers. Consequently, her revenues are not affected. Majority drivers have both higher precision and higher expectation; therefore, their gain due to a good review is relatively low. On the basis of the discount factor from the estimation of the cost of effort ($\beta = 0.94$), the discounted sum of gains from 30 future rides adds up to 0.53 EUR, whereas for a typical minority driver, the sum of gains increases fivefold to 2.5 EUR.

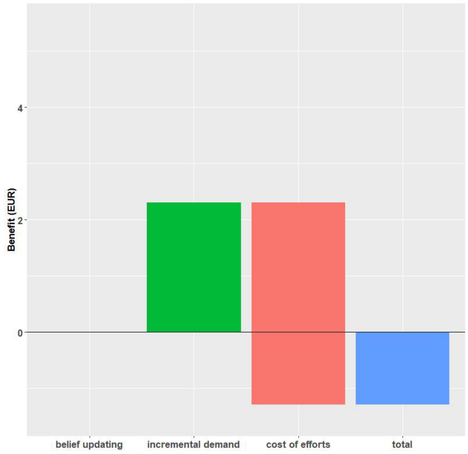
Second counterfactual: value of a more precise reputation system. A greater precision of the reputation system has three distinct effects. First, it increases the returns from efforts, since passengers are better able to assess the quality they observe, and convey reliable information to future passengers through the reputation system.[16] These incremental efforts induce an increase in demand (see demand model in Section 4.1, Equation 4.1), which is profitable to drivers. However, as we observe and estimate in Section 4.2, the increased precision also induces driver to exert more efforts, which is costly (see Equation 4.13). Finally, the increased precision allows drivers to reveal their type faster, and in particular to correct the beliefs of the market, that may be biased downwards. This aspect constitutes a benefit to minority users.

Figure 4.8 illustrates the results of this counterfactual for minority (left panel) and majority (right panel) drivers. The left-hand bar represents the benefits that accrue to a typical minority drivers in the form of belief updating. The second bar is the increase in demand. The third bar corresponds to increased provision of (costly) efforts. The last bar is the net benefit of these three forces. Interestingly, the cost of effort provision (3rd bar) overwhelms the direct benefit from efforts stemming from increased demand (2nd bar). Overall, a doubling of the precision of the reputation system would result in an increase in cumulative profits of minority drivers of 1.7 EUR, most of which would stem from the updating of beliefs (+3 EUR). In the case of majorities (right panel), no biased beliefs need to be corrected. Overall, majority drivers are worse off: this is an illustration of the "rat race" (Holmström, 1999), whereby drivers are trapped into supplying the equilibrium level of effort that is required of them. In our case, this rate race benefits passengers more than drivers.

[16] A perfectly uninformative (imprecise) reputation system would render efforts worthless.



(a) Minority



(b) Majority

Figure 4.8: Expected increment in cumulative pro
fits for minority (left) and majority drivers (right), when the precision of the reputation system doubles.

We conclude that increasing the precision of the reputation system, e.g., by displaying more detailed profiles, asking passengers to report their experience according to pre-specified criteria or give them the possibility to give more precise grades, may spawn considerable benefits to users and especially the populations facing overly pessimistic beliefs. In turn, the increase in precision may also benefit the platform itself, thanks to better matching.

5 Conclusion

While minority users have been documented to face discrimination in a number of online marketplaces, the role of reputation systems in overcoming discrimination has been less studied. Our empirical analysis uses unique data on listings on a popular online carpooling platform to show that minority users achieve lower economic outcomes. Their listings are less popular, they sell fewer seats, and they receive lower revenue. However, this effect is concentrated during the first interactions on the platform. Building a reputation helps minority drivers narrow the gap. We obtain this result via various econometric techniques and show that these market effects are not due to underperforming minority drivers exiting the market. We also provide a study of career dynamics, enabling us to separate statistical discrimination from erroneous beliefs, and find that statistical updating of rationally held beliefs can explain only part of the gap. We attribute the remaining part to erroneous beliefs.

Passengers are willing to change their minds about minority drivers when they see reviews. This observation highlights the importance of a well-designed reputation system for revealing information and indicates that the early stages of reputation-building are particularly important. A platform aiming to alleviate discrimination should, therefore, concentrate its efforts on the quality of its reputation system during the first interactions.

In future research, we will aim to further exploit our dataset. Preliminary results show a significant degree of social homophily in the data. Indeed, passengers tend to ride preferentially with drivers from the same population and them give higher ratings. While this factor is unlikely to alter the insights of the present paper, measuring homophily could, in itself, be an interesting research project. Additionally, we are aware that more recent reviews are more prominent than older reviews. We believe this may encourage drivers to continue exerting effort, even if they have already accumulated many reviews. The impact of the prominence of recent reviews may, therefore, require further investigation.

While this Chapter can be considered as final work, this is part of an ongoing, broader research project. As a consequence, some of the results presented may be modified in the corresponding paper in the future.

Bibliography

Abadie, A. and Imbens, G. W. (2016). Matching on the Estimated Propensity Score. *Econometrica*.

Abrahao, B., Parigi, P., Gupta, A., and Cook, K. S. (2017). Reputation offsets trust judgments based on social biases among airbnb users. *Proceedings of the National Academy of Sciences*, 114(37):9848–9853.

Agrawal, A., Lacetera, N., and Lyons, E. (2016). Does standardized information in online markets disproportionately benefit job applicants from less developed countries? *Journal of international Economics*, 103:1–12.

Alesina, A., Michalopoulos, S., and Papaioannou, E. (2016). Ethnic inequality. *Journal of Political Economy*, 124(2):428–488.

Altonji, J. G. and Pierret, C. R. (2001). Employer Learning and Statistical Discrimination EMPLOYER LEARNING AND STATISTICAL DISCRIMINATION*. *Source: The Quarterly Journal of Economics*, 116(1):313–350.

Arrow, K. (1973). The Theory of Discrimination.

Banerjee, A. and Munshi, K. (2004). How efficiently is capital allocated? evidence from the knitted garment industry in tirupur. *The Review of Economic Studies*, 71(1):19–42.

Bar-Isaac, H. and Tadelis, S. (2008). Seller Reputation. *Foundations and Trends® in Microeconomics*, 4(4):273–351.

Bartoš, V., Bauer, M., Chytilová, J., and Matějka, F. (2016). Attention discrimination: Theory and field experiments with monitoring information acquisition. *American Economic Review*, 106(6):1437–75.

Becker, G. (1971). The economics of discrimination. *University of Chicago Press Economics Books*.

Blablacar (2018). Bringing People Bringing People. Technical report.

Bohren, J. A., Imas, A., and Rosenberg, M. (2018). The dynamics of discrimination: Theory and evidence.

Bolton, G. E., Katok, E., and Ockenfels, A. (2004). How Effective Are Electronic Reputation Mechanisms? An Experimental Investigation. *Management Science*, 50(11):1587–1602.

Cabral, L. L., Hortacsu, A., and Hortaçsu, A. (2010). The dynamics of seller reputation:Evidence from eBay. *The Journal of Industrial Economics*, LVIII(1):54–78.

Castillo, M., Petrie, R., Torero, M., and Vesterlund, L. (2013). Gender differences in bargaining outcomes: A field experiment on discrimination. *Journal of Public Economics*, 99:35–48.

Chiappori, P.-A., Salanie, B., and Valentin, J. (1999). Early starters versus late beginners. *Journal of Political Economy*, 107(4):731–760.

Cook, C., Diamond, R., Hall, J., List, J. A., Oyer, P., et al. (2018). The gender earnings gap in the gig economy: Evidence from over a million rideshare drivers. *Upubliceret paper. Tilgængelig på: https://web. stanford. edu/˜ diamondr/UberPayGap. pdf. Besøgt*, pages 26–04.

Dellarocas, C. and Wood, C. A. (2008). The Sound of Silence in Online Feedback: Estimating Trading Risks in the Presence of Reporting Bias. *Management Science*, 54(3):460–476.

Edelman, B., Luca, M., and Svirsky, D. (2017). Racial Discrimination in the Sharing Economy: Evidence from a Field Experiment. *American Economic Journal: Applied Economics*, 9(2):1–22.

Edelman, B. G. and Luca, M. (2014). Digital Discrimination: The Case of Airbnb.com. *SSRN Electronic Journal*.

Fang, H. and Moro, A. (2011). Theories of statistical discrimination and affirmative action: A survey. In *Handbook of social economics*, volume 1, pages 133–200. Elsevier.

Farajallah, M., Hammond, R. G., and PPnard, T. (2016). What Drives Pricing Behavior in Peer-to-Peer Markets? Evidence from the Carsharing Platform BlaBlaCar. *SSRN Electronic Journal*.

Gandhi, A., Lu, Z., and Shi, X. (2013). Estimating demand for differentiated products with error in market shares. Technical report, cemmap working paper, Centre for Microdata Methods and Practice.

Ge, Y., Knittel, C., MacKenzie, D., and Zoepf, S. (2016). Racial and Gender Discrimination in Transportation Network Companies. *NBER Working Paper Series*, (22776):1–38.

Goddard, T., Kahn, K. B., and Adkins, A. (2015). Racial bias in driver yielding behavior at crosswalks. *Transportation Research Part F: Traffic Psychology and Behaviour*, 33:1–6.

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching As An Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *The Review of Economic Studies*.

Hjort, J. (2014). Ethnic divisions and production in firms. *The Quarterly Journal of Economics*, 129(4):1899–1946.

Holmström, B. (1999). Managerial Incentive Problems: A Dynamic Perspective. *Review of Economic Studies*.

Iacus, S. M., King, G., and Porro, G. (2009). cem : Software for Coarsened Exact Matching. *Journal of Statistical Software*.

Jolivet, G., Jullien, B., and Postel-Vinay, F. (2016). Reputation and prices on the e-market: Evidence from a major French platform. *International Journal of Industrial Organization*, 45:59–75.

Jullien, B. and Park, I. U. (2014). New, like new, or very good? Reputation and credibility. *Review of Economic Studies*, 81(4):1543–1574.

Laouenan, M. and Rathelot, R. (2017). Ethnic Discrimination on an Online Marketplace of Vacation Rentals. *working paper*.

Liu, Q. and Skrzypacz, A. (2014). Limited records and reputation bubbles. *Journal of Economic Theory*, 151(1):2–29.

Livingston, J. A. (2005). How Valuable Is a Good Reputation? A Sample Selection Model of Internet Auctions. *Review of Economics and Statistics*, 87(September):453–465.

Mayzlin, D., Dover, Y., and Chevalier, J. (2014). Promotional reviews: An empirical investigation of online review manipulation.

Mazzella, F. and Sundararajan, A. (2016). Entering the Trust Age. Technical report.

Nosko, C. and Tadelis, S. (2015). The Limits of Reputation in Platform Markets: An Empirical Analysis and Field Experiment. *NBER Working Paper Series*, page 20830.

Phelps, E. S. (1972). The Statistical theory of Racism and Sexism. *American Economic Review*, 62(4):659–661.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*.

Sarsons, H. (2017). Interpreting Signals in the Labor Market: Evidence from Medical Referrals. *Job Market Paper*.

Spagnolo, G. (2012). Reputation, competition, and entry in procurement. *International Journal of Industrial Organization*, 30(3):291–296.

Tjaden, J. D., Schwemmer, C., and Khadjavi, M. (2018). Ride with me -ethnic discrimination, social markets, and the sharing economy. *European Sociological Review*, 34(4):418–432.

Zervas, G., Proserpio, D., and Byers, J. (2015). A First Look at Online Reputation on Airbnb, Where Every Stay is Above Average. *Where Every Stay is Above ...*, pages 1–22.

A Navigation on Blablacar.fr

First, users type in the origin, destination and date of the ride they are seeking. They then see a list of rides meeting their request (Figure 4.9). They may then click on specific postings to have more details about the ride (Figure 4.10). Finally they may either see the profile of the driver (Figure 4.11) or proceed directly to payment. BlaBlaCar service fees are a function of the price posted by the driver. The fees and their evolution over time are shown on Figure 4.12.

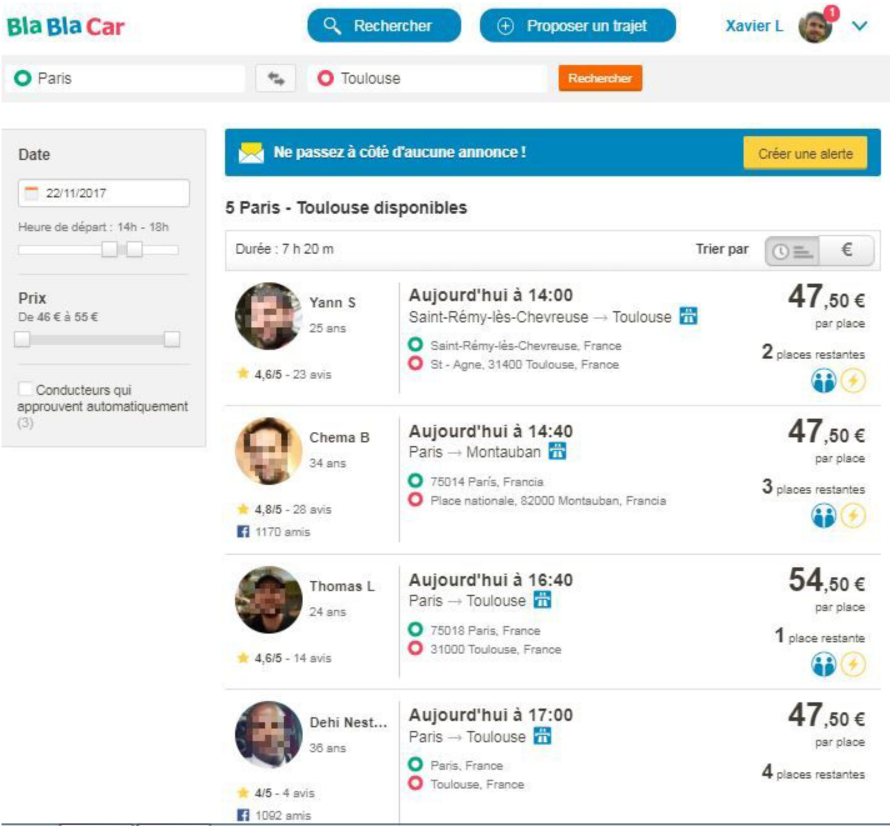


Figure 4.9: Listing offered on a given route

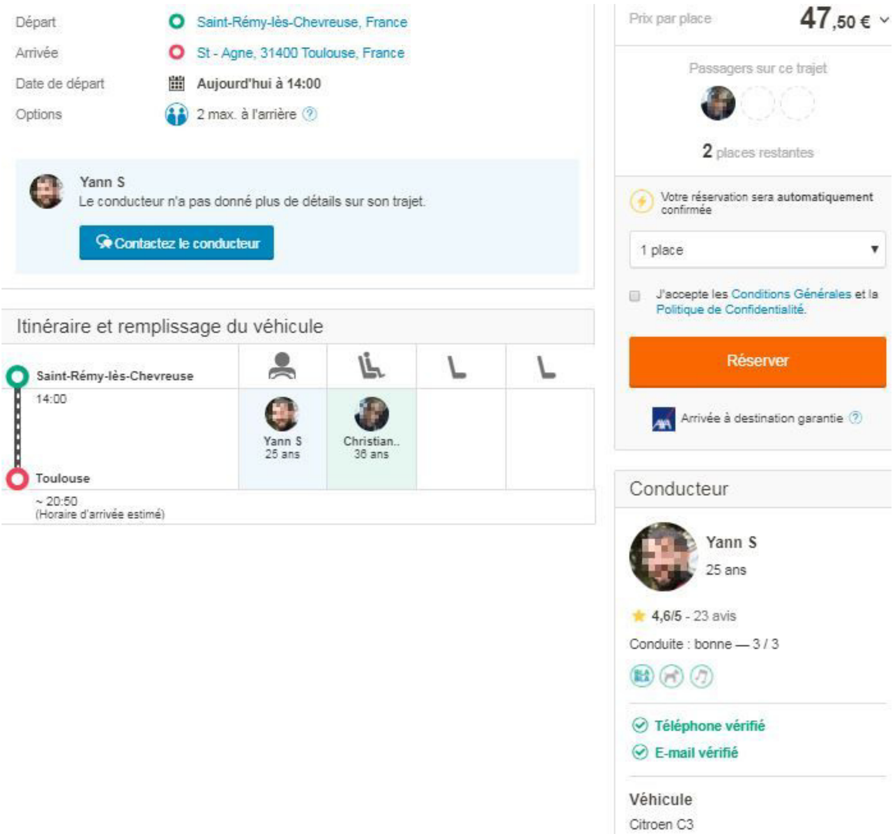


Figure 4.10: Details of a posting

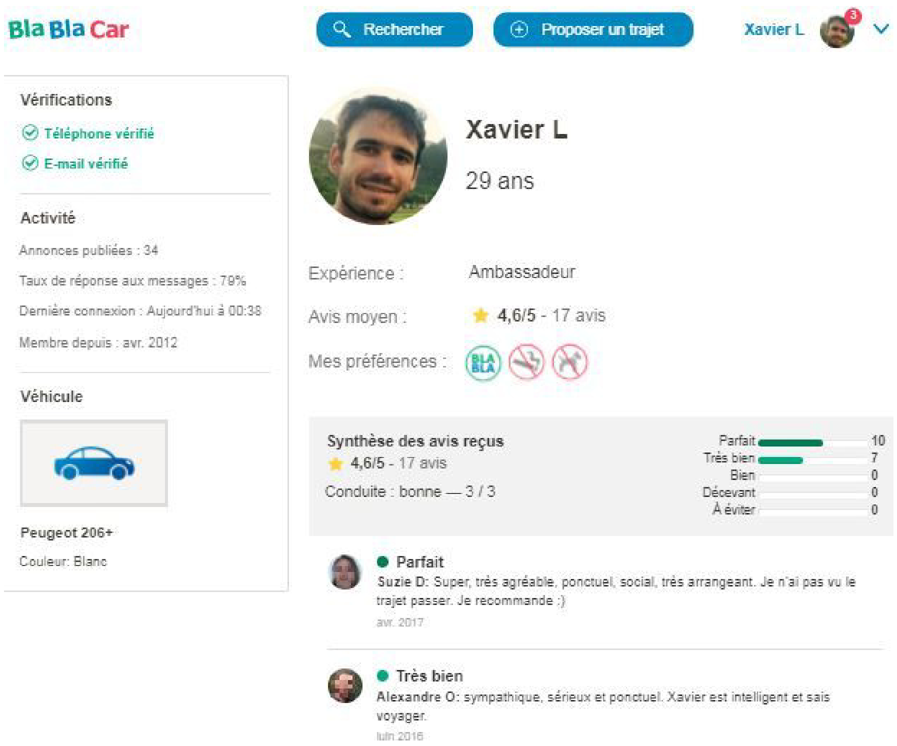


Figure 4.11: A driver's profile

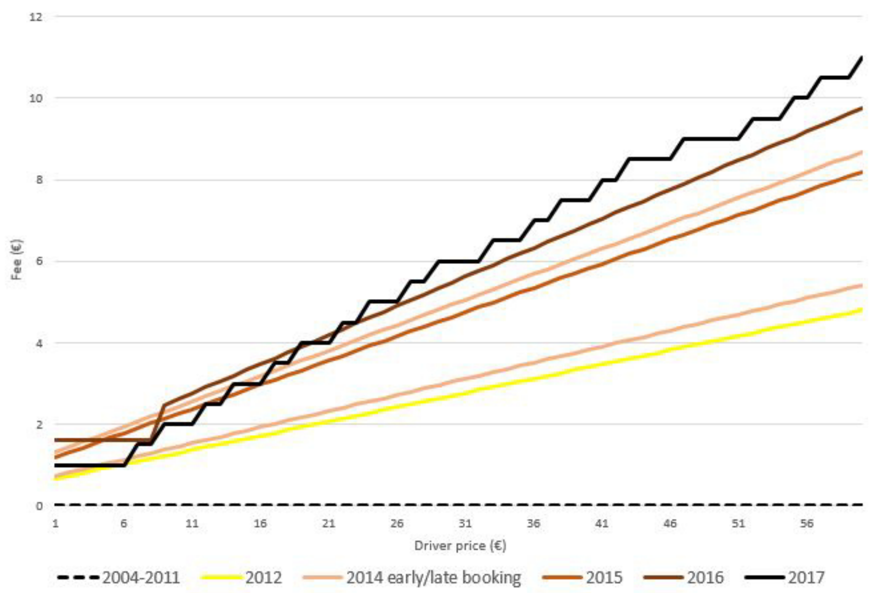


Figure 4.12: Evolution of service fees on BlaBlaCar over time

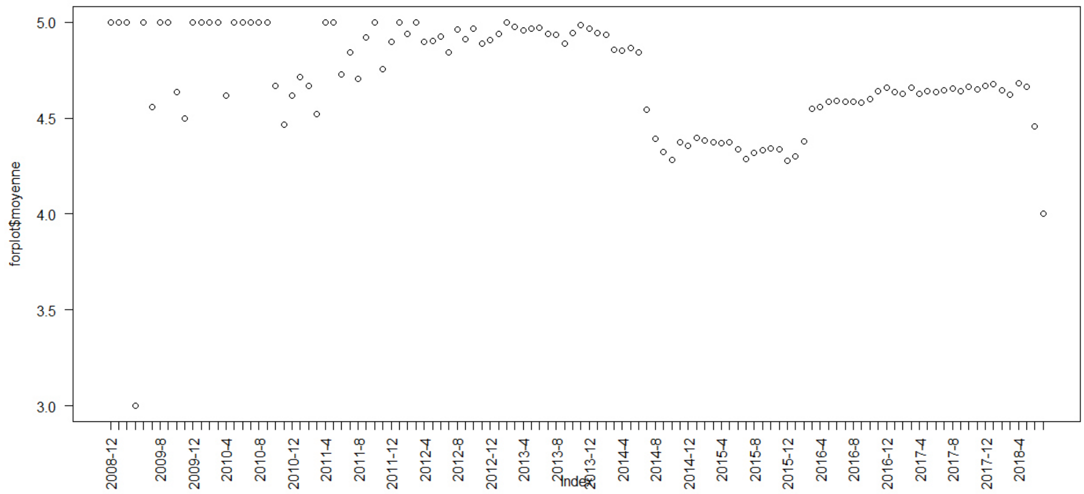


Figure 4.13: Average rating for drivers with more than 30 reviews

B Changes in the BlaBlaCar reputation system

In our study of the evolution of ratings, we have abstracted from the potential changes in the design of the reputation system of BlaBlaCar. Some drivers in our sample have been BlaBlaCar users since December 2008, and others joined only a few days before our crawler observes their listing. These drivers may have operated under different market characteristics. See Figure 4.13 for the evolution of the average rating over time. Until the end of 2013, ratings were either 1 or 5. In early 2014, these binary ratings were translated to the current 5-star system. Later, in February 2016, the wording of the ratings was changed: *excellent* became *tres bien* and *extraordinaire* became *parfait*. The impact of this change on the average rating is clear. People are more likely to call a ride *parfait* than they were to call it *extraordinaire*. Finally, these changes influenced the informativeness of the reputation system; see Figure 4.14. The dotted black line shows HHI (which is a measure of dispersion and, hence, the informativeness of the classifiers): the smaller the HHI is, the more informative the classifier. The ratings in the period 2014-2016 were the most informative. Dark green, green, orange, pink, and red represent the shares of 5s, 4s, 3s, 2s and 1s, respectively. Initially, there is a considerable noise because we have very few observations: fewer than 100 per month before October 2009 and more than 30.000 per month starting in 2017.

These changes are important because they affected the ratings that we study, but they

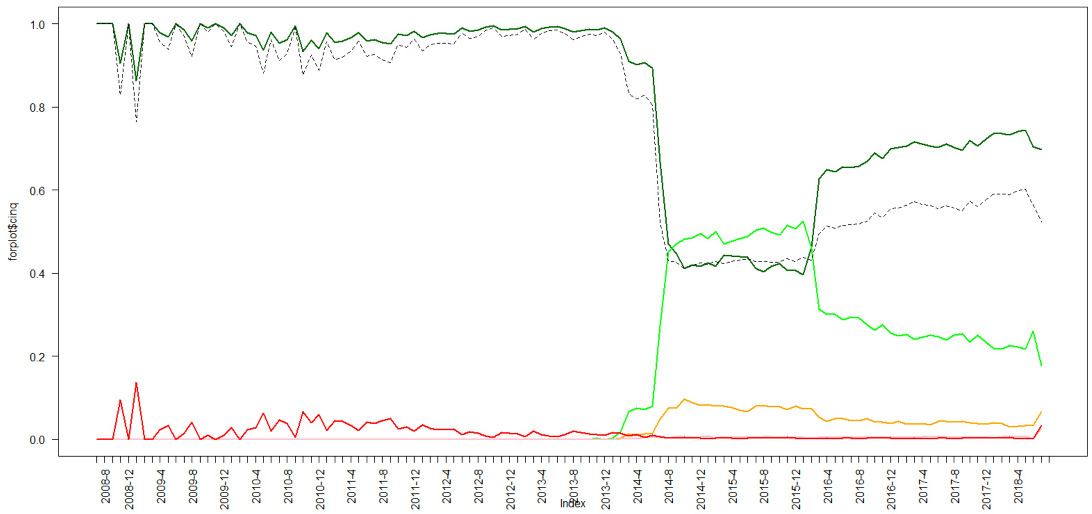


Figure 4.14: Informativeness of the reputation system and share of grades received. Dark green=5, light green=4, orange=3, pink=2, red=1.

also show how important the design of the review system is. One may be concerned that some of the decline in effort that we characterized could be due to changes in the reputation system. In a sample restricted to drivers who joined after all the changes in the reputation system were made, we can reproduce the same patterns of behavior; however, we lose a considerable number of observations. Thus, we argue that the evolution of ratings throughout the career of a driver on BlaBlaCar is due to the economic logic of career concerns rather than exogenous changes in the reputation system.

C Classification method for gender and ethnicity

Driver-specific characteristics are key determinants in our model. Hence, the drivers' type must be identified as accurately as possible. Specifically, gender and ethnicity are critical to our analysis. To identify these characteristics, both prospective riders and the econometrician consider two relevant sources of information: the first name and the profile picture. For the first time in the literature, we use both sources of information to infer gender and ethnicity.

C.1 Classification of gender

As a first source of information, we use the name of the driver. We match our dataset of driver names with those of various sources relating first names with ethnicity. The French Government repository of names (www.data.gouv.fr/fr/datasets/liste-de-prenoms) constitutes our main source of information. We complement it with data from other sources.[17] This data enables us to identify the gender of almost 80% of drivers, along with 3% unisex names.

We then use facial recognition to identify gender whenever a picture is available. This process also enable us to identify 80 % of the dataset. By combining these two processes, we can directly identify gender for 95% of the dataset.

Further, we use facial recognition to enrich and correct our name database. Rare or misspelled names (either because the driver registered under a nickname or because of translation variations if the name is not originally French) can be re-classified. This process can identify the gender of some drivers whose names are not listed in our inventories and who do not have a picture (or for pictures where gender is not easily identified) because other drivers with the same name may have posted identifiable pictures. This method brings the precision of our gender identification as high as 99%. Figure 4.15 summarizes our identification process.

[17] www.signification-prenom.net, www.madame.lefigaro.fr/prenoms/origine

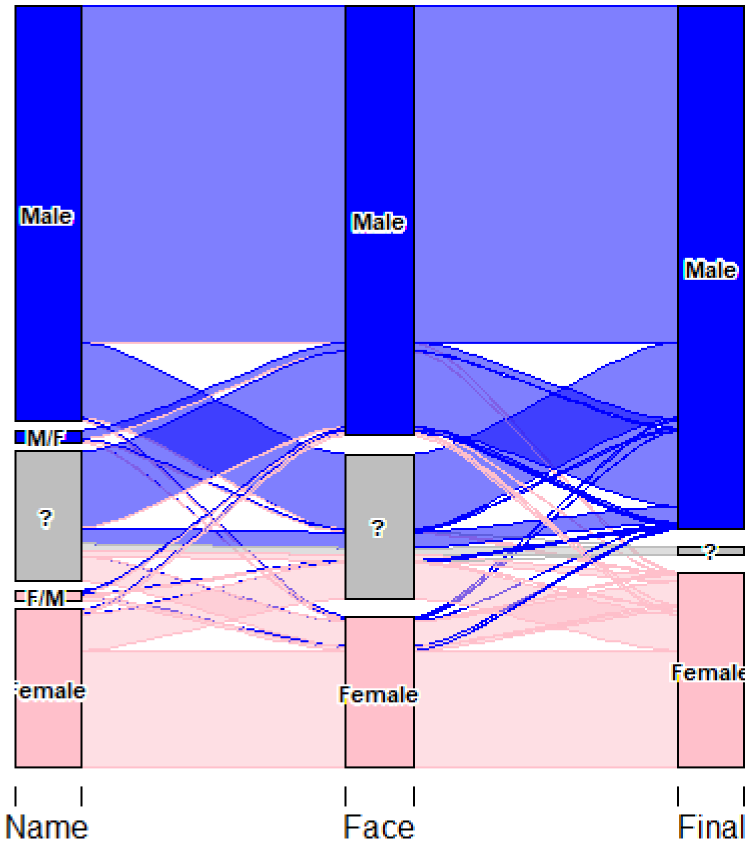


Figure 4.15: Classification process for gender: by name (left), by facial recognition (center) and final classification (right)

C.2 Classification of ethnicity

Our methodology for the identification of ethnicity follows the same steps and uses the same sources as those for gender classification. First, we collect the origins of names from the data sources mentioned above. This provides the ethnicity of approximately 81% of our sample. However, names might not be a perfect indicator of ethnicity. Indeed, many visible minorities have a French name for various historical reasons or because they have foreign origins but were born in France. In that case, a simple name analysis would classify them as non-minorities while they might belong to a minority on the basis of their skin color.

Hence, we use facial recognition to identify ethnicity whenever a picture is available. The algorithm proposes an ethnicity for 80 % of the dataset. However, only "white", "black", "Asian" , and "Latino" ethnicities are proposed. People of Arabic origin are classified as "white". Hence, facial recognition is useful only to classify drivers more accurately between african origin, and majority or arabic origin.

We also use facial recognition to enrich and correct our name repository and to better identify ethnicity. Overall, facial recognition reclassifies 2.5% of drivers with a French name and 5% of drivers with Arabic names (predominantly Muslim names) into Sub-Saharan ethnicity. Including facial recognition increases the sample size for minorities from 11% to 14% of our sample. Figure 4.16 summarizes our identification process.

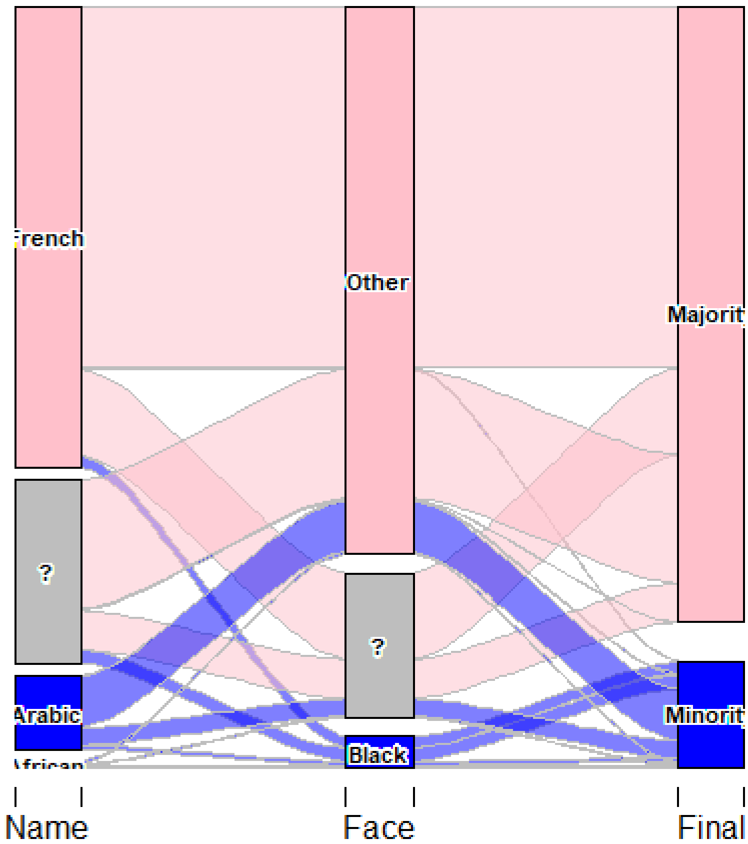


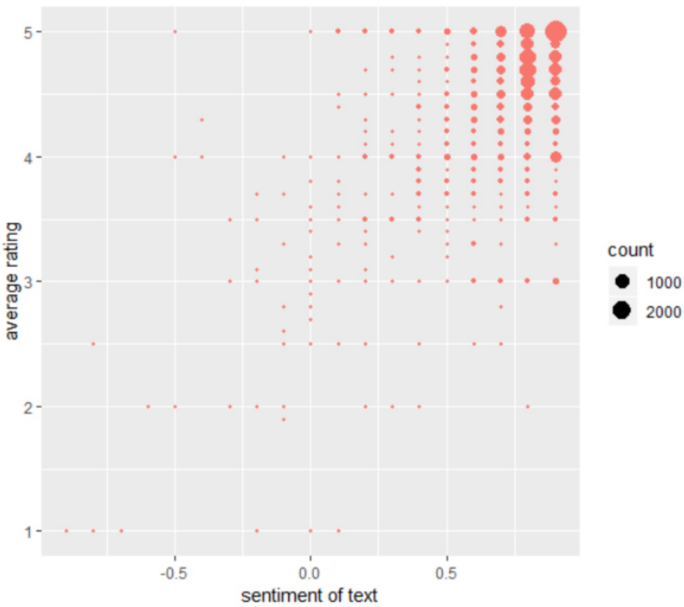
Figure 4.16: Classification process for ethnicity: by name analysis (left), by facial recognition (center) and final classification (right)

D Ratings as a measure of passenger satisfaction

The body of the paper analyses the effect of reputation on the sole basis of ratings. It assumes that ratings have enough informational content to allow passengers to form a belief about the quality of a driver.

In this Appendix, we show that ratings are indeed likely to be a good summary of passengers' experience. To do so, we analyze whether good reviews (i.e. reviews with a high rating) are more likely to be associated with a written comment that has a positive connotation than bad reviews. For that purpose, we use the Cloud Natural Language processing tools of Google, a tool that implements machine learning to reveal the structure and meaning of text. We are particularly interested in the sentiment of the review, with a measure between -1 (very negative) and 1 (very positive). A positive correlation between sentiment and rating is a prerequiste of our analysis: as Figure 4.17a illustrates, the written comments reveal that the aspects that matter to passengers are rather subjective, and are not easy to segment into definite categories.

(a)



(b)

Figure 4.17: Textual analysis of the comments (18000 randomly selected drivers).
(a) Font size is propositional to frequency of word use in comments.
(b) Average rating and average sentiment of comment are highly correlated.

The correlation between the grade given, and the sentiment of the text of the review very high, as is suggested by Figure 4.17b. We therefore conclude that ratings are a satisfactory a measure of performance for the purpose of the present paper.

E Railways strike as a quasi-experiment:

In the main text, we have used the number of reviews as a measure of the career stage of drivers. We argue that this is a relevant measure to track progress in the career because these are the signals that are observed by passengers. A drawback of this approach is that it is endogenous, in the sense that the number of reviews depends on the past success of a given driver. In other words, someone who is considered as a bad driver will never collect more reviews, therefore will not be able to signal her quality. In order to establish a causal relationship between reviews and success on the market, we need an exogenous variation in the number of reviews. This is the aim of this section.
During our sample period, in the spring of 2018, French railways workers went on a national strike. Amongst other reasons, opposition to the plans to liberalize the European railway market and in particular opening the French market to competition was the cause of the strike. As illustrated in Figure 4.18, the strike was organized as a sequence of two days of disruptions every five days.

Figure 4.18: Days of strike. Source: *le Parisien*

Blablacar and railways are in direct competition. A negative supply shock happening on the railway market transmits to Blablacar as a positive demand shock. For example, in April 2018 5 mln passengers traveled on Blablacar, up from the 1.5 mln average; the

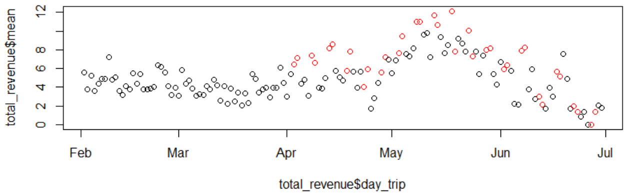


Figure 4.20: Average revenue. Days of strike in red.

number of booking requests increased six-fold.[18] In our dataset, the days of strike are also characterized by extraordinary demand. Figures 4.19 and 4.20 show an increase in the number of sold seats and revenue made during days of the strike.

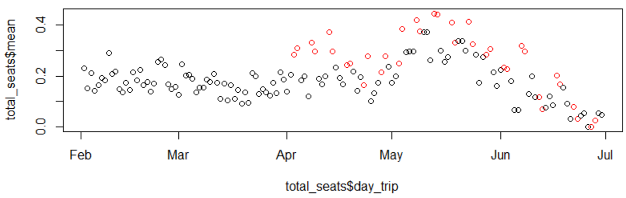


Figure 4.19: Average number of sold seats. Days of strike in red.

[H] During these days, most of the drivers were fully booked; even, drivers that would usually struggle to attract passengers were able to sell seats and receive reviews. We treat strikes as a source of exogenous variation and perform a difference-in-differences analysis. Some drivers used Blablacar several times during the strike, thus we define the variables of interest in the following way: $before$ will indicate trips made before ever driving during the strike; $after$ indicates period after the last time of driving during the strike; as *treated* we will consider minority drivers, who drove at least once during the strike– the control group is non-minority drivers who also drove during the strike. Finally, *did* is a product of *treated* and $after$. We removed days of strike. Figure 4.8 presents the results with revenue as a dependent variable.

The variable of interest is *did*. We see that it is positive and significant across all specifications. The magnitude is much higher than the impact of the minority status alone. In our interpretation this is because *did* captures two effects: the correction of

[18] Source: www.lemonde.fr/economie/article/2018/04/03/les-transports-alternatifs-grands-gagnants-de-la-greve-a-la-sncf_5279932_3234.html

	Dependent variable: revenue		
	(1)	(2)	(3)
treated	−0.454 (0.346)	−0.419 (0.415)	−0.371 (0.414)
after	−3.603 (3.671)	−3.814 (4.019)	−4.006 (4.017)
did	1.179* (0.645)	1.390* (0.711)	1.372* (0.711)
minority	−0.542*** (0.086)	−0.367*** (0.098)	−0.304*** (0.098)
male	0.332*** (0.068)	0.266*** (0.077)	0.335*** (0.077)
Driver characteristics			x
Listing characteristics		x	x
Route effects	x	x	x
Time effects	x	x	x
Observations	297,189	240,656	240,656
Residual Std. Error	15.909 (df = 296996)	15.980 (df = 240459)	15.969 (df = 240454)
F Statistic	65.115*** (df = 192; 296996)	53.219*** (df = 196; 240459)	53.634*** (df = 201; 240454)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4.8: Impact of strikes on the economic performance of minorities

beliefs about quality of these minority drivers, and also an increase in the number of reviews. We believe that strikes provide us with evidence pointing towards causal link between reviews and improvement of performance between minority drivers.

F Oversampling of minorities for short-notice rides

Due to our scraping method, it cannot be excluded that our sample provides a slightly biased representation of listings. Indeed, the program takes snapshots of listings displayed on the website at a given point time. However, rides that are already full are no longer displayed on the platform. This means our data collection may undersample the particularly attractive rides that would sell out very fast, or those corresponding to times when demand is much higher than supply. This wouldn't be an issue if both minorities and non-minorities were affected the same way by this sampling bias. However, as we show in this paper the minority status does impact the attractiveness of a given listing. Therefore, minorities who may be perceived as posting less attractive rides remain longer on display and may therefore be over-represented in our sample. Therefore, our minority gap estimates should be understood as lower bounds. Indeed, minorities are compared to a pool constituted of non-minorities that are not so good as to have sold out their seats extremely fast. Table 4.21 shows that minority drivers represent a specially high share of rides that are posted on a short notice, a possible sign that non-minority drivers have sold their seats faster. For trips posted with more notice, we believe our sample is indeed representative of the actual participants on blablacar. Indeed, most of the rides –either from minorities or not – still have more than one empty seat, which means that most listings and indeed collected. In fact, Blablacar informs drivers that most passengers book rides only a few days in advance.

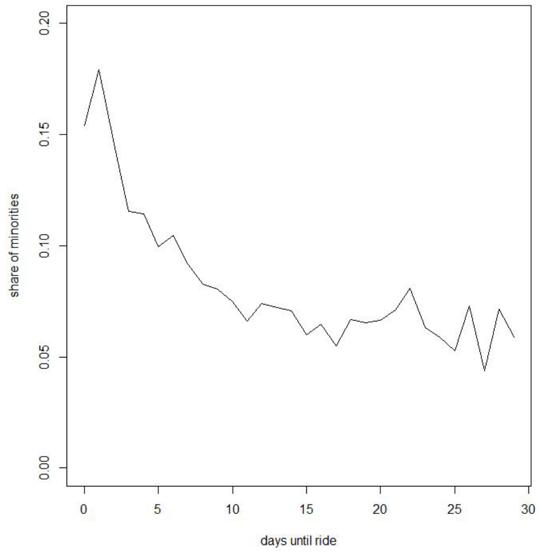


Figure 4.21: Share of minorities in sample as a function of number of days between posting and departure

This is true despite the fact minorities tend to allow for automatic confirmation more frequently than non-minorities (18% of drivers with automatic confirmation are minorities, while they represent only 12% of the drivers with manual confirmation).

Reputation effect

G Matching Analysis

This project, likewise most in the literature, uses non-experimental data for evaluating the impact of minority status. Hence, estimates of the impact of being a minority may suffer from a bias of the selection on the non-observables. There is a growing, mostly theoretical, literature on the use of matching techniques to address this issue. Rosenbaum and Rubin (1983) and Heckman et al. (1997) demonstrate that this bias can be greatly reduced by use of various matching techniques. Some of their properties are discussed by Abadie and Imbens (2016). A similar methodology has been applied in Sarsons (2017). [19]

The objective of matching exercise is to test the robustness of results from the standard

[19] We use matching software developed by Iacus et al. (2009).

Table 4.9: Revenue regressed over driver and ride characteristics

	Dependent variable:		
	revenue		
	(1)	(2)	(3)
minority	−0.622*** (0.142)	−0.450** (0.178)	−0.235 (0.168)
driver age	−0.033*** (0.004)	−0.026*** (0.005)	−0.008 (0.005)
# reviews	0.233*** (0.029)	0.078*** (0.021)	0.014*** (0.001)
male	−0.278** (0.108)	−0.198 (0.131)	0.213 (0.151)
seniority (months)	−0.006*** (0.002)	−0.016*** (0.003)	−0.029*** (0.003)
hours till ride	−0.015*** (0.0005)	−0.019*** (0.001)	−0.028*** (0.001)
posted since (days)	0.215*** (0.007)	0.304*** (0.009)	0.345*** (0.009)
posts per month	0.044 (0.040)	−0.133*** (0.049)	−0.409*** (0.034)
bio (# words)	0.009 (0.005)	0.010 (0.006)	0.0001 (0.007)
car price	−0.018* (0.010)	−0.006 (0.012)	−0.019 (0.012)
competition	0.006*** (0.002)	0.004* (0.002)	0.005*** (0.002)
duration public transport	−0.219 (0.512)	−0.976 (0.653)	−2.862*** (0.786)
km	0.003 (0.003)	0.010*** (0.004)	0.016*** (0.004)
night_dayday	0.402** (0.194)	0.771*** (0.239)	0.575** (0.246)
night_daynight	−1.024*** (0.299)	−0.859** (0.391)	−1.669*** (0.378)
train strike	2.758*** (0.294)	2.980*** (0.358)	3.106*** (0.547)
ride (# words)	0.030*** (0.004)	0.018*** (0.004)	0.013*** (0.004)
picture	0.198 (0.278)	0.091 (0.432)	−1.295*** (0.413)
automatic confirm	3.380*** (0.107)	3.126*** (0.126)	2.929*** (0.126)
weekday	−0.509** (0.202)	−0.221 (0.248)	−1.172*** (0.244)
driver_blabla2	−0.070 (0.325)	0.579 (0.423)	1.233** (0.498)
driver_blabla3	−0.460 (0.371)	0.629 (0.475)	1.146** (0.538)
travel cost	0.017** (0.008)	0.005 (0.011)	0.020 (0.012)
revenu median			
night_dayday:weekday	0.096 (0.238)	−0.237 (0.291)	0.243 (0.293)
night_daynight:weekday	0.013 (0.368)	−0.613 (0.474)	0.360 (0.454)
Constant	3.283*** (0.962)	3.561*** (1.306)	12.756*** (1.744)
Time effects	X	X	X
Trip effects	X	X	X
Observations	82,563	65,013	68,505
R^2	0.060	0.070	0.096
Adjusted R^2	0.058	0.068	0.094
Residual Std. Error	13.720 (df = 82413)	14.825 (df = 64863)	15.428 (df = 68355)
F Statistic	35.305*** (df = 149; 82413)	32.917*** (df = 149; 64863)	48.521*** (df = 149; 68355)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4.10: Sold seats regressed over driver and ride characteristics

	Dependent variable:		
	seats sold		
	(1)	(2)	(3)
minority	−0.024*** (0.005)	−0.014** (0.006)	−0.0003 (0.007)
driver age	−0.001*** (0.0001)	−0.001*** (0.0002)	−0.0004** (0.0002)
# reviews	0.008*** (0.001)	0.004*** (0.001)	0.001*** (0.00004)
male	−0.005 (0.004)	−0.002 (0.004)	0.011* (0.006)
seniority months	−0.0002** (0.0001)	−0.001*** (0.0001)	−0.001*** (0.0001)
hours till ride	−0.001*** (0.00002)	−0.001*** (0.00002)	−0.001*** (0.00003)
posted since	0.008*** (0.0002)	0.012*** (0.0003)	0.014*** (0.0004)
posts per month	0.001 (0.001)	−0.007*** (0.002)	−0.020*** (0.001)
length bio	0.0001 (0.0002)	0.0001 (0.0002)	−0.0001 (0.0003)
car price	−0.0002 (0.0003)	0.0002 (0.0004)	−0.00003 (0.0004)
competition	0.0002*** (0.0001)	0.0001** (0.0001)	0.0002** (0.0001)
public transport	10.937** (5.263)	1.626 (6.970)	10.995 (9.310)
km	−0.00004 (0.0001)	−0.0001 (0.0001)	0.00003 (0.0001)
night dayday	0.013** (0.006)	0.024*** (0.008)	0.019** (0.010)
night_daynight	−0.043*** (0.010)	−0.030** (0.013)	−0.079*** (0.015)
train strike	0.103*** (0.010)	0.139*** (0.013)	0.151*** (0.022)
length ride	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)
picture	−0.002 (0.009)	−0.007 (0.014)	−0.026* (0.015)
automatic confirm	0.134*** (0.004)	0.125*** (0.004)	0.134*** (0.005)
weekday	−0.029*** (0.007)	−0.028*** (0.009)	−0.074*** (0.009)
night_dayday:weekday	0.010 (0.008)	−0.002 (0.010)	0.025** (0.011)
night_daynight:weekday	0.005 (0.012)	−0.024 (0.016)	0.022 (0.018)
Constant	0.136** (0.060)	0.278*** (0.084)	0.470*** (0.124)
Time effects	X	X	X
Trip effects	X	X	X
Observations	91,870	72,597	76,999
R^2	0.066	0.066	0.083
Adjusted R^2	0.064	0.064	0.081
Residual Std. Error	0.479 (df = 91709)	0.538 (df = 72437)	0.636 (df = 76839)
F Statistic	40.382*** (df = 160; 91709)	32.225*** (df = 159; 72437)	43.731*** (df = 159; 76839)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4.11: Number of clicks regressed over driver and ride characteristics

	Dependent variable:		
	number of clicks		
	(1)	(2)	(3)
minority	−0.469*** (0.155)	−0.375** (0.176)	0.011 (0.157)
driver age	−0.074*** (0.004)	−0.062*** (0.005)	−0.033*** (0.005)
# reviews	−0.026 (0.031)	0.052** (0.020)	0.017*** (0.001)
gender	−1.490*** (0.118)	−1.740*** (0.129)	−0.918*** (0.140)
seniority (months)	−0.007*** (0.002)	−0.016*** (0.003)	−0.044*** (0.003)
hours till ride	−0.034*** (0.001)	−0.038*** (0.001)	−0.045*** (0.001)
posted since	1.195*** (0.008)	1.348*** (0.010)	1.210*** (0.009)
post per month	−0.186*** (0.044)	−0.470*** (0.048)	−0.779*** (0.032)
bio (# words)	0.002 (0.006)	0.005 (0.006)	−0.004 (0.006)
car price	0.013 (0.010)	0.016 (0.012)	−0.0004 (0.011)
competition	0.011*** (0.002)	0.009*** (0.002)	0.012*** (0.002)
public transport	621.016*** (172.629)	463.648** (201.726)	210.257 (227.734)
km	0.016*** (0.002)	0.016*** (0.002)	0.014*** (0.003)
night_dayday	−0.711*** (0.209)	0.495** (0.236)	0.630*** (0.227)
night_daynight	−0.075 (0.328)	0.595 (0.386)	−1.286*** (0.351)
train strike	5.238*** (0.330)	4.812*** (0.364)	4.838*** (0.533)
ride (# words)	0.053*** (0.004)	0.038*** (0.004)	0.011*** (0.003)
picture	1.228*** (0.282)	0.237 (0.389)	−0.882** (0.355)
automatic confirm	−0.195* (0.116)	−0.455*** (0.124)	−1.560*** (0.118)
weekday	−1.252*** (0.218)	−0.145 (0.245)	−0.894*** (0.225)
night_dayday:weekday	1.395*** (0.257)	0.058 (0.287)	0.664** (0.271)
night_daynight:weekday	−0.161 (0.403)	−0.594 (0.469)	0.847** (0.423)
Constant	6.838*** (1.990)	7.960*** (2.446)	18.424*** (3.060)
Observations	87,004	69,163	73,834
R^2	0.250	0.259	0.254
Adjusted R^2	0.249	0.257	0.253
Residual Std. Error	15.279 (df = 86843)	15.085 (df = 69003)	14.899 (df = 73675)
F Statistic	180.918*** (df = 160; 86843)	151.472*** (df = 159; 69003)	158.901*** (df = 158; 73675)
Note:			*p<0.1; **p<0.05; ***p<0.01

OLS of Section 3.2. We will firstly estimate propensity scores for each of the observations and discard these with extreme values. Secondly, we will perform matching of the minority and non-minority subsamples on driver-specific variables. We will execute both exact matching and coarsened matching. Finally, we will regress model using the matched sample, controlling for listing-specific characteristics.
The propensity score is a logistic regression with minority status being dependent variables and following controls: the price of a car, driver's age, number of posts per month, picture dummy, length of biography, gender, fuel consumption of the car and whether the driver is talkative. The results are displayed in Table 4.12. Minority drivers are more likely to be a young male and to enjoy conversations. They have on average more expensive cars that consume more fuel; their profiles are also shorter. We delete 5% smallest and 5% largest propensity scores, in this way we delete observations for which we are unlikely to find a counterpart.

Table 4.12: Propensity score table

	Dependent variable:
	f minority
car price	0.024*** (0.001)
driver age	−0.033*** (0.001)
post per month	0.058*** (0.003)
picture	0.078*** (0.023)
length bio	−0.013*** (0.0005)
f gender	0.952*** (0.019)
consumption	0.140*** (0.010)
driver blabla	0.329*** (0.014)
Constant	−2.965*** (0.063)
Observations	195,333
Log Likelihood	−75,005.150
Akaike Inf. Crit.	150,028.300
Note:	*p<0.1; **p<0.05; ***p<0.01

Exact matching

is performed on all driver's characteristics for which we have estimated the logistic regression. In our sample, it means that we have 8809 minority drivers matched with 22617 non-minority drivers. As entrants, we will label minority drivers with less than five reviews and as incumbents (experienced users) these with more than 50 reviews. In the case of exact matching, the definition of an incumbent is extended to drivers with more than 30 reviews so as to increase the size of the group. From Table 4.13 we can see that

Table 4.13: Economic outcomes of entrants, exact matching

	Dependent variable		
	number of clicks	Revenue	Taken seats
minority	-1.2546*** (0.341)	-0.69684** (0.221)	-0.0258*** (0.007)
hours until ride	-0.0107 (0.009)	-0.0109 (0.006)	-0.0005* (0.0002)
posted since	2.0561 *** (0.225)	0.2721 (0.145)	0.0059 (0.005)
competition	0.0249 ***(0.005)	0.003*** (0.569)	0.0005*** (0.0001)
day	0.3792 (0.349)	0.5492* (0.226)	0.0121 (0.012)
night	0.8578 (0.517)	-1.2120*** (0.335)	-0.0492 *** (0.005)
notice	−0.4786* (0.122)	-0.0027 (0.145)	0.0031 (0.023)
Matched Observations	19,112		

Note: Trip fixed effects not reported *p<0.05; **p<0.01; ***p<0.001

even after the matching procedure, minority entrant drivers are facing discrimination. We repeat the same process for drivers with reputation. The results in Table 4.14 reveal the reputation effect; minority status when users are experienced is insignificant for all measures of economic outcome.

Table 4.14: Economic outcomes of incumbent drivers, exact matching

	Dependent variable		
	number of clicks	Revenue	Taken seats
minority	-0.2876 (0.383)	0.1409 (0.303)	0.0106 (0.012)
hours untill ride	-0.0340** (0.0117)	0.0112 (0.009)	0.0009* (0.0004)
posted since	1.8896*** (0.282)	1.341*** (0.223)	0.0626 *** (0.009)
competition	0.0168 **(0.005)	0.0076 (0.004)	0.0003 (0.0002)
day	0.1916 (0.394)	0.0322 (0.311)	0.0177 (0.012)
night	0.5573 (0.634)	-1.9742*** (0.500)	-0.0829*** (0.019)
notice	-0.1398 (0.280)	-0.8167 *** (0.221)	-0.0436 *** (0.008)
Matched Observations	12314		

Note: Trip fixed effects not reported *p<0.05; **p<0.01; ***p<0.001

Coarsened Matching

Coarsened Matching is a method used to increase the number of matched observations. We introduce bins in which we will match non-binary covariates: age of the driver, the price of a car, number of posts per month, length of bio and fuel consumption of the car. Choice of cutoffs influences the precision of matching procedure as well as the number of matched observations; we match within a quartile for each of the variables. In this way, we match 14146 minority drivers with 45959 nonminority ones, which is almost a twofold increase. We present only the coefficient of minority status (Table 4.15). In this

Table 4.15: Economic outcomes entrants and incumbents, coarsened matching

	Dependent variable		
	number of clicks	Revenue	Taken seats
minority (entrant)	-0.9276 *** (0.271)	-0.6032*** (0.180)	-0.0191** (0.006)
minority (incumbent)	-0.3883 (0.303)	0.0330 (0.229)	-0.0084 (0.010)
Matched Observations (both models)	57,853		

*p<0.1; **p<0.05; ***p<0.01

coarsely matched sample, we also see a clear reputation effect. Minority entrants have lower economic outcomes, however after they build reputation most of the effect goes away. These results depend on cut-offs for labeling as entrants/ incumbents, as well as on the selection of bins for coarsened matching; they are however robust to local changes.

Table 4.16: Propensity score

	Dependent variable:
	f minority
car price	0.024*** (0.001)
driver age	−0.033*** (0.001)
post per month	0.058*** (0.003)
picture	0.078*** (0.023)
length bio	−0.013*** (0.0005)
f gender	0.952*** (0.019)
consumption	0.140*** (0.010)
driver blabla	0.329*** (0.014)
Constant	−2.965*** (0.063)
Observations	195,333
Log Likelihood	−75,005.150
Akaike Inf. Crit.	150,028.300
Note:	*p<0.1; **p<0.05; ***p<0.01

H Detailed panel data results

Table 4.17: Number of clicks received by the listing

	Dependent variable: number of clicks		
	Pooled	Between	Random
minority	0.288 (0.202)	0.409 (0.275)	0.317 (0.236)
entrant	−0.995*** (0.143)	−0.811*** (0.179)	−0.764*** (0.155)
minority*entrant	−0.678* (0.353)	−0.692 (0.449)	−0.717* (0.387)
driver's age	−0.036*** (0.005)	−0.038*** (0.006)	−0.036*** (0.006)
talkative	0.220* (0.123)	0.363** (0.156)	0.282** (0.141)
male	−1.074*** (0.142)	−1.105*** (0.171)	−1.128*** (0.159)
hours until ride	−0.028*** (0.0005)	−0.023*** (0.001)	−0.029*** (0.0005)
posted since	1.136*** (0.010)	1.068*** (0.016)	1.172*** (0.010)
bio (# words)	−0.002 (0.004)	−0.003 (0.005)	−0.002 (0.004)
car price	−0.018 (0.012)	−0.031** (0.015)	−0.021 (0.014)
competition	0.036*** (0.002)	0.035*** (0.003)	0.034*** (0.002)
median revenue	−0.00002 (0.00003)	−0.0001* (0.00004)	−0.00000 (0.00003)
public transport ratio	−0.909 (7.222)	−1.761 (10.861)	−2.131 (7.765)
km	0.007*** (0.0004)	0.006*** (0.001)	0.006*** (0.0004)
day	0.538** (0.231)	0.574 (0.364)	0.462** (0.231)
night	−0.605* (0.357)	−1.134* (0.581)	−0.763** (0.358)
train strike	3.269*** (0.325)	3.049*** (0.538)	3.545*** (0.319)
ride (# words)	0.018*** (0.002)	0.021*** (0.002)	0.020*** (0.002)
picture	0.246 (0.201)	0.494* (0.260)	0.496** (0.230)
automatic acceptance	−1.334*** (0.122)	−1.299*** (0.164)	−1.307*** (0.132)
weekday	−0.018 (0.236)	−0.457 (0.387)	0.112 (0.237)
consumption	0.278*** (0.084)	0.377*** (0.106)	0.303*** (0.095)
day*weekday	0.465 (0.284)	0.925** (0.460)	0.389 (0.284)
night*weekday	−0.018 (0.444)	1.577** (0.746)	0.094 (0.443)
Constant	11.748*** (0.880)	10.465*** (1.234)	11.477*** (0.948)
Observations	56,760	22,794	56,760
R^2	0.244	0.220	0.262
Adjusted R^2	0.244	0.219	0.261
F Statistic	495.292*** (df = 37; 56722)	173.642*** (df = 37; 22756)	543.306*** (df = 37; 56722)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4.18: Number of seats solds in the listing

	Dependent variable: sold seats		
	Pooled	Between	Random
minority	0.002 (0.009)	0.016 (0.011)	0.002 (0.009)
entrant	−0.060*** (0.011)	−0.058*** (0.012)	−0.059*** (0.011)
minority*entrant	−0.035** (0.016)	−0.041** (0.018)	−0.035** (0.016)
male	0.005 (0.008)	0.004 (0.009)	0.004 (0.008)
driver's age	−0.0004* (0.0002)	−0.0003 (0.0002)	−0.0004* (0.0002)
talkative	0.001 (0.005)	0.003 (0.006)	0.001 (0.006)
hours until ride	−0.001*** (0.00002)	−0.001*** (0.00003)	−0.001*** (0.00002)
posted since	0.016*** (0.0004)	0.012*** (0.001)	0.016*** (0.0004)
bio (# words)	−0.0001 (0.0002)	−0.0003 (0.0002)	−0.0001 (0.0002)
car price	−0.0003 (0.001)	−0.001 (0.001)	−0.0004 (0.001)
competition	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)
median revenue	0.00000*** (0.00000)	0.00001*** (0.00000)	0.00000*** (0.00000)
public transport ratio	−0.146 (0.318)	−0.566 (0.440)	−0.147 (0.322)
km	−0.00002 (0.00002)	−0.0001** (0.00002)	−0.00002 (0.00002)
day	0.015 (0.010)	0.004 (0.015)	0.015 (0.010)
night	−0.048*** (0.016)	−0.062*** (0.023)	−0.048*** (0.016)
train strike	0.126*** (0.014)	0.110*** (0.022)	0.128*** (0.014)
ride (# words)	0.0004*** (0.0001)	0.0004*** (0.0001)	0.0004*** (0.0001)
picture	0.002 (0.009)	0.015 (0.010)	0.003 (0.009)
automatic acceptance	0.109*** (0.005)	0.108*** (0.007)	0.109*** (0.005)
weekday	−0.045*** (0.010)	−0.059*** (0.016)	−0.045*** (0.010)
consumption	0.020*** (0.004)	0.021*** (0.004)	0.020*** (0.004)
minority*entrant	−0.035** (0.016)	−0.041** (0.018)	−0.035** (0.016)
entrant*male	−0.016 (0.013)	−0.022 (0.014)	−0.015 (0.013)
day*weekday	0.019 (0.012)	0.034* (0.019)	0.019 (0.013)
night*weekday	−0.020 (0.019)	0.012 (0.030)	−0.020 (0.020)
Constant	0.180*** (0.039)	0.158*** (0.050)	0.175*** (0.039)
Observations	59,359	23,076	59,359
R^2	0.089	0.085	0.088
Adjusted R^2	0.088	0.083	0.087
F Statistic	152.507*** (df = 38; 59320)	56.087*** (df = 38; 23037)	150.026*** (df = 38; 59320)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4.19: Revenue secured by the listing

	Dependent variable: revenue		
	Pooled	Between	Random
minority	−0.334 (0.213)	0.022 (0.275)	−0.272 (0.228)
entrant	−1.387*** (0.150)	−1.452*** (0.179)	−1.308*** (0.155)
minority*entrant	−0.680* (0.372)	−0.866* (0.448)	−0.741* (0.387)
driver's age	−0.006 (0.005)	−0.002 (0.006)	−0.005 (0.005)
talkative	0.020 (0.129)	0.065 (0.155)	0.026 (0.137)
male	−0.201 (0.148)	−0.307* (0.170)	−0.240 (0.156)
hours untill ride	−0.018*** (0.0005)	−0.016*** (0.001)	−0.019*** (0.0005)
posted since	0.371*** (0.010)	0.290*** (0.014)	0.375*** (0.010)
bio (# words)	−0.001 (0.004)	−0.005 (0.005)	−0.001 (0.004)
car price	−0.007 (0.013)	−0.022 (0.015)	−0.010 (0.013)
competition	0.024*** (0.002)	0.024*** (0.003)	0.024*** (0.002)
median revenue	0.0002*** (0.00003)	0.0003*** (0.00004)	0.0002*** (0.00003)
public transport ratio	−33.375*** (7.569)	−40.181*** (10.934)	−33.318*** (7.835)
km	0.013*** (0.0004)	0.011*** (0.001)	0.013*** (0.0004)
day	0.410* (0.243)	0.445 (0.367)	0.400 (0.244)
night	−1.341*** (0.373)	−2.091*** (0.579)	−1.300*** (0.376)
train strike	2.367*** (0.339)	1.779*** (0.543)	2.429*** (0.338)
ride (# words)	0.007*** (0.002)	0.008*** (0.002)	0.007*** (0.002)
picture	0.087 (0.212)	0.366 (0.260)	0.170 (0.225)
automatic acceptance	2.064*** (0.128)	2.012*** (0.164)	2.104*** (0.133)
weekday	−0.847*** (0.249)	−1.142*** (0.390)	−0.828*** (0.251)
consumption	0.315*** (0.088)	0.340*** (0.106)	0.325*** (0.093)
minority*entrant	−0.680* (0.372)	−0.866* (0.448)	−0.741* (0.387)
day*weekday	0.317 (0.299)	0.446 (0.465)	0.290 (0.300)
night*weekday	−0.215 (0.465)	0.938 (0.745)	−0.232 (0.467)
Constant	−1.089 (0.926)	−2.287* (1.239)	−1.200 (0.957)
Observations	58,621	23,018	58,621
R^2	0.095	0.093	0.094
Adjusted R^2	0.094	0.091	0.093
F Statistic	165.658*** (df = 37; 58583)	63.359*** (df = 37; 22980)	163.313*** (df = 37; 58583)

Note: *p<0.1; **p<0.05; ***p<0.01

I Robustness check: subsample of accomplished rides

Our data is collected by choosing a route at random and collecting data on all available listings at a given time. Therefore, in our sample there are listings that have been posted just a couple of seconds before we have seen it, and some that have been available for days. Many of the listings that we have observed haven't sold a single seat so far. There are two important consequences of this, firstly we have a selected sample, where we expect to see listings that are on average less attractive than those that sold out (we have discussed this in Appendix F). Secondly, our demand model approximated choice probability with market share. Arguably, rides that have been just posted have a higher than zero choice probability. We have dealt with it two-fold, either by adding a small number to the market share, or by lumping all zero market shares to the outside option. Here, we provide another robustness check by using a supplementary dataset. Our objective is to argue that we observe zero market shares because of our data collection process rather than because some drivers have too low quality to be able to sell even at very low price.

We have used Blablacar API[20] to collect data on all rides that have been available on a given route in a given day, and their final performance measures, ie. how many seats have been sold overall by a given driver. The API does not allow us to open drivers profiles, however, some of them we have observed earlier and are in our core dataset. We select these drivers. Summary statistics are in Table 4.20. The second visit corresponds to the data from the API, which we collect after completion of the ride.

Table 4.20: Summary stats API data

Statistic	N	Mean	St. Dev.	Min	Max
price (1st visit)	90,333	33.909	17.476	2.000	134.500
price (2nd visit)	90,333	34.794	17.346	2.000	122.500
seats sold (1st visit)	90,333	0.360	0.655	0	4
seats sold (2nd visit)	90,333	1.382	1.176	0	4
number of clicks (1st visit)	89,302	29.705	35.911	0	822
number of clicks (2nd visit)	90,333	70.085	59.733	0	1,018

We observe that the average number of seats sold is 1.4, which is much higher than in our core dataset.

J Belief updating with discrete reports

The market forms a prior based on driver's characteristics which are observed on her profile, later on as market receives signals about the performance of the driver, beliefs are updated. Holmström (1999) assumes the prior to be normally distributed with mean

[20] Application Programming interface: https://dev.blablacar.com/

and variance: $\eta \sim N(m_1, h_1)$; also, he assumes that signals are distributed normally and continously. This leads to a formation of posterior beliefs:

$$\mathbf{E}\left[\eta|z_s\right] = \frac{h_1 m_1 + h_\epsilon \sum_{s_1}^{t} z_s}{h_1 + t h_\epsilon} \tag{A4.17}$$

However, we cannot apply this formula directly because the evaluations are not continuous. Suppose that realizations of output are continuous, but the signals received by the market are discrete. However, there is an objective rule, such that if a realizations falls within a given interval there is always the same grade given: for example, a grade 3 is given when the observed realized output falls within the interval 2.5-3.5, a grade of 5 is given when the observed output is above 4.5. This allows us to calculate marginal probabilities, and characterize the posterior belief, so:

$$\pi(\theta|y) = \frac{f_{y|\theta}(y|\theta)\pi(\theta)}{\int_\Theta f_{y|\theta}(y|\theta)\pi(\theta)d(\theta)} \equiv f_{y|\theta}(y|\theta)\pi(\theta) \tag{A4.18}$$

,where $\pi(\theta|y)$ denotes a probability of being of type θ while getting a grade y and $f_{y|\theta}(y|\theta)$ is a conditional probability of a conditional distribution, the empirical counteraprt of equation (4) is

$$\mathbf{E}\left[\theta|Y = y\right] = \frac{P(Y = y \text{ and } \eta = \theta)}{P(Y = y)} * m_i$$

We are currently improving our estimates to account for this.

K How do drivers respond?

Exerting effort to build reputation Our reduced-form empirics suggest that reputation is valuable for users; it allows them to signal their individual quality. It has an additional benefit for minority drivers because it allows them to mitigate discrimination. The more valuable is the reputation, the more effort drivers will exert to establish it. In our dataset, we do not observe efforts directly (we estimate them with a structural model in Section 4), but we have a few variables that can suggest an increased effort. Making detours or accepting pets is costly for the drivers, but appreciated by the passengers. Table 4.21 shows that drivers with few reviews are more likely to exert additional efforts and that it is more the case for minority drivers, for whom reputation matters more.

	Dependent variable:	
	Detour	Allows pets
reviews (#)	-0.003^{***} (0.0002)	-0.0004^{*} (0.0002)
minority*reviews (#)	-0.002^{***} (0.0005)	-0.005^{***} (0.001)
Driver effects	X	X
Ride effects	X	X
Time effects	X	X
Trip effects	X	X
Observations	55,621	107,749
Akaike Inf. Crit.	57,863.370	105,043.600
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4.21: Proxies for effort, selected variables, logistic regressions.

All three regression have a binary dependent variable that indicates whether a driver is willing to make a detour for the convenience of a passenger, or accept a pet in the car. We see that users with no reviews are more likely to take these efforts, which is consistent with the interpretation of reputation building investments. Furthermore, this effect is more significant for minority drivers. We interpret it by noting that minority drivers value reputation more, and are therefore more likely to make this additional effort.

Secondly, we can follow the evolution of grades. Figure 4.22 panel (a) shows the average grade at different stages of a "career" (the first bullet on the left is an average first grade). We see that drivers typically receive higher ratings at the begining. Panel (b) shows the difference between the t-th review, and the average of the grades received by the driver after the 15th ride. We observe that minorities show a greater entrant premium than non-minorities, suggesting that more efforts are made when they enter the platform.[21]

[21] Another way to "invest" in reputation is to lower the price upon entering the platform. We study an incentive to do so in a parallel research project.

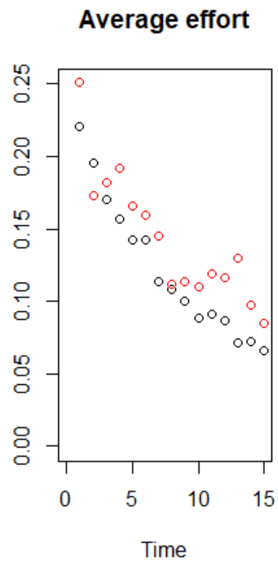


Figure 4.22: Average efforts as a function of seniority. Minority Entrants make greater efforts. Non-minorities: black dots; minorities: red dots.