SUPPLEMENTAL APPENDIX

# Global giants and local stars: How changes in brand ownership affect competition

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## A Modules

Since our original data from GMID does not classify brands into greater detail than beer and spirits, we have enlisted several sources of this information. First, some brands (e.g. Seagram's Gin and Gin Lubuski) have their type revealed as part of the brand name. This also helps us identify low-alcohol and low-calorie beers. Second, we used a definition of modules similar to that employed by Nielsen's Homescan and the Iowa Liquor Control Board. Third, we aggregated detailed beer "styles" provided by the online rating site `ratebeer.com` into Nielsen-level modules. So doing, we have classified 4908 brands into modules, about 85% of the beer and spirits brands in GMID, and 97% of the sales for classifiable brands.[1]

## B Extensive margins for brands and markets

In this section, we document the very important cross-sectional extensive margin of market entry as well as the relatively small entry rates over time for beer and spirits.

Figure B.1 illustrates a few features of the distribution of brands across markets that play important roles in determining the outcomes of brand ownership changes in the beer

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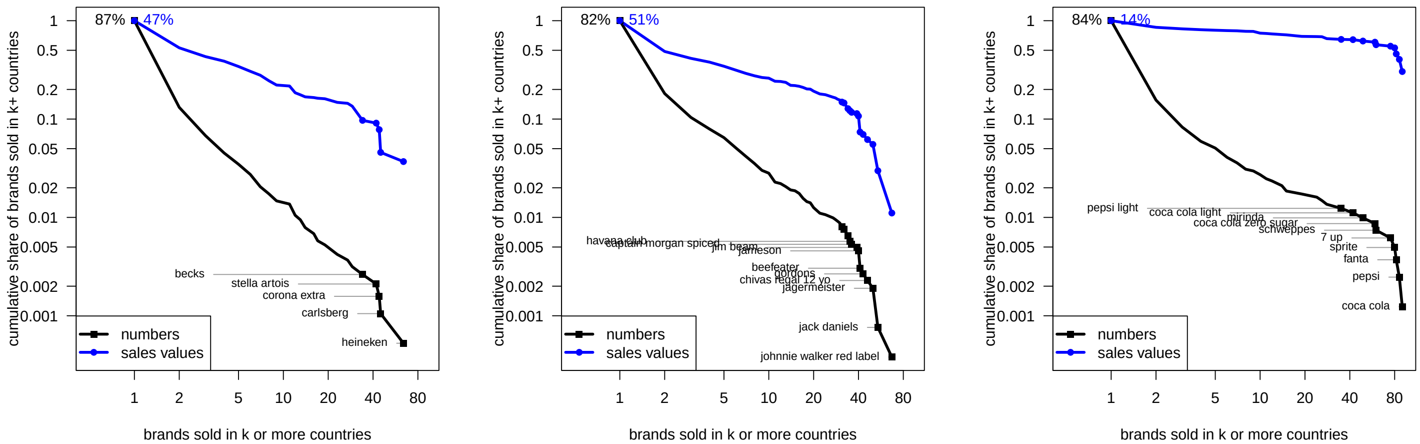
[1] The brands GMID lumps together as "Others" could only be assigned to modules by assumption.

Figure B.1: Global giants are rare




(a) Beer (b) Spirits (c) Carbonates

Notes: Symbols mark brands sold in $> 30$ countries. Log scales on both axes. Calculations exclude fringe brands since their counts and destinations are not known.

and spirits industries. First, echoing a result shown repeatedly for exporters, a "happy few" brands are offered in many destinations and account for a disproportionate share of sales.[2]

Table B.1 investigates the entry margin, through which firms add or drop brands in selected markets or altogether. The first panel considers the fraction of brands that are new each year (the add rate) whereas the second column is the fraction of brands that existed in the previous year but not the current year. Add rates are slightly higher (2.3 and 3.4%) than drop rates (1.6–3%). The drop rate does not fall in beer after acquisition and it does not fall much for spirits. Rather than the "buy to kill" pattern observed by Cunningham et al. (2019) in the pharmaceutical industry, firms in the beer and spirits industries "buy to keep." This difference is just what industrial organization would predict. While it can make sense to drop products in their early stages to save on development costs, most beer and spirits brands are already established in their markets. Therefore it makes more sense to simply raise their prices than to drop them. Note that add rates are not formulated in a way that would allow us to compare them before and and after acquisitions.

Panel (b) of table B.1 calculates add rates as a fraction of the number of potential market-years where the brand is absent in the previous period. The add rates are so small because there are 78 countries where brands might be offered but the vast majority are sold at home only. The second column shows the rate at which brands exit markets.

[2]Bernard et al. (2007) show these patterns in US data, Mayer and Ottaviano (2007) coin the term and show that the pattern holds for many countries.

Table B.1: Adding and dropping brands in markets and overall: Beer and Spirits

| Sample frame | Add rate (in percent) | Drop rate (in percent) |
|---|---|---|
| **Beer** | | |
| **(a) Brand-level births and deaths:** | | |
| All brand/years | 3.44 | 2.55 |
| Brands changing owners: before | NA | 2.44 |
| Brands changing owners: after | NA | 2.94 |
| **(b) Brands added/dropped in a market:** | | |
| All brand/market/years | 0.06 | 2.64 |
| Continuing brands | 0.02 | 0.76 |
| Brands changing owners: before | 0.03 | 0.60 |
| Brands changing owners: after | 0.03 | 1.36 |
| **Spirits** | | |
| **(a) Brand-level births and deaths:** | | |
| All brand/years | 2.26 | 1.98 |
| Brands changing owners: before | NA | 2.09 |
| Brands changing owners: after | NA | 1.62 |
| **(b) Brands added/dropped in a market:** | | |
| All brand/market/years | 0.05 | 1.85 |
| Continuing brands | 0.03 | 0.72 |
| Brands changing owners: before | 0.04 | 0.88 |
| Brands changing owners: after | 0.04 | 1.50 |

Here the denominator is much smaller. Nevertheless, only two to three percent of brands are dropped from a market each year. Most of those exiting brands disappear because the brand itself was dropped. Among continuing brands, the exit rate is less than one percent. There is a slight uptick after acquisitions but over 98% of brand-market combinations are retained on a year-by-year basis.

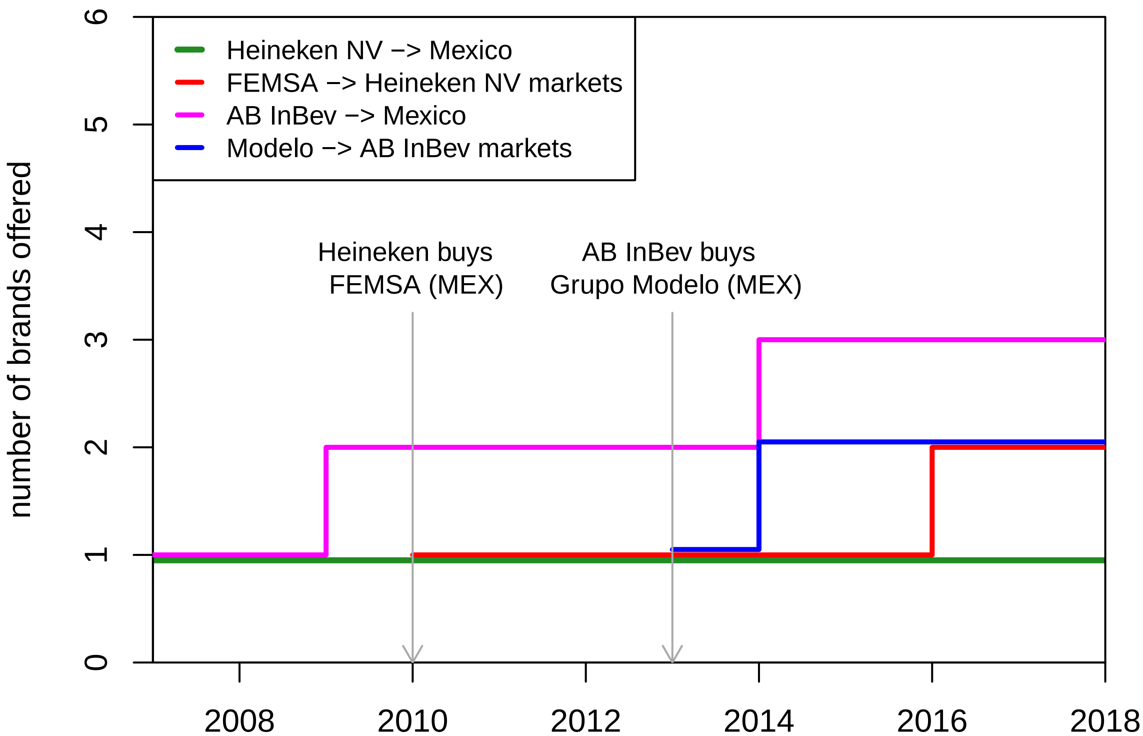
Overall, we see high stability over time in which brands are offered and where they exceed the 0.1% market share threshold. Furthermore, changes in ownership do not seem to spur significant elimination of brands. Nor do they spur increased distribution across markets. This last result might seem surprising given the importance of global giants. It is based on the whole sample and might hide interesting dynamics for the big players. We therefore consider two case studies that demonstrate the limited extensive margin exhibited even by major acquisitions carried out by the largest firms in each industry.

Figure B.2(a) displays the temporal relationship between brand offerings in the buyer and target markets before and after two acquisitions of large Mexican beer makers. Before Heineken purchased FEMSA, it already sold Heineken in Mexico. Similarly AB InBev already offered Budweiser and Bud Light. After the 2010 and 2013 takeovers, Heineken did not bring any of its 302 brands to Mexico and AB InBev brought only its Belgian flagship brand, Stella Artois. In the reverse direction, Heineken ultimately put two of FEMSA's 14 brands in markets FEMSA did not previously serve. AB InBev put two of Grupo Modelo's 13 brands in a total of four new markets by 2018 (out of a possible 73 markets).

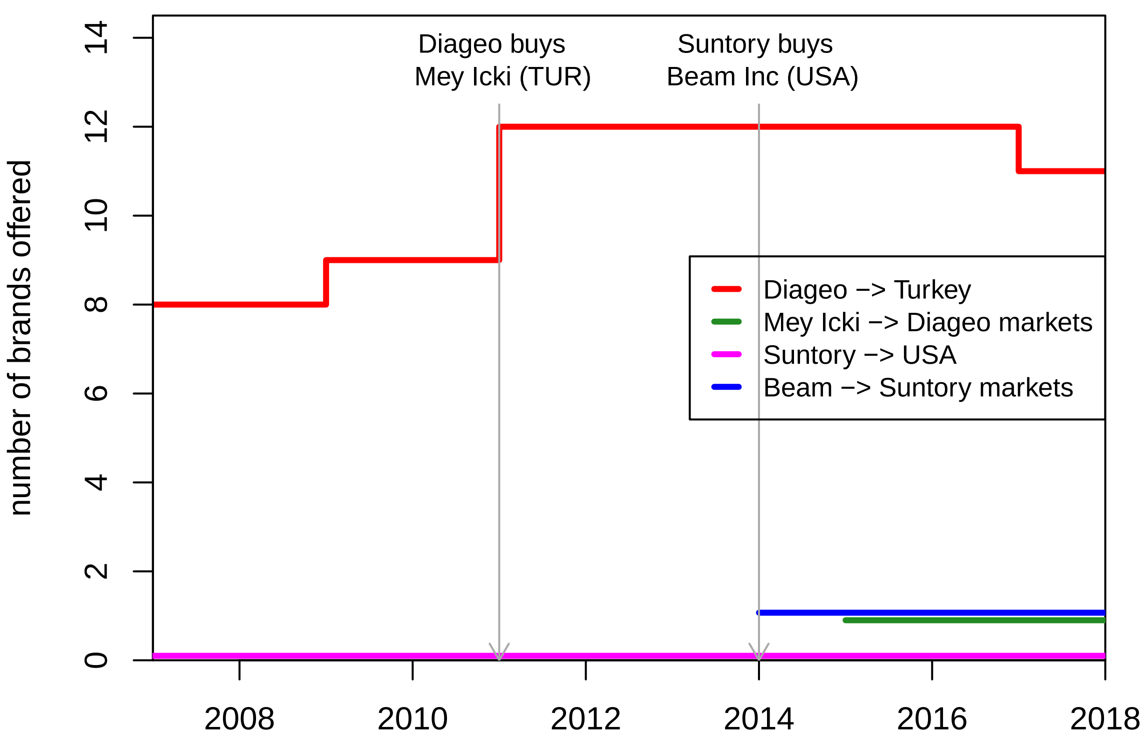
Figure B.2(b) examines two similar cases from the spirits category. Again we see very little in the way of expansion along the extensive margin following the acquisition of the Turkish Mey Icki, by Diageo, and of the acquisition of the American company Beam Inc. by Suntory. Diageo, owner of 204 brands, added just three new brands in Turkey (though it later dropped one) and took Mey Icki's top brand, Yeni Raki, to Bulgaria only (though it could potentially have offered it in 73 countries). None of Suntory's 63 brands had sales in the US that are large enough to cross the 0.1% GMID threshold—before or after the purchase of Beam.

These case studies focus on acquisitions which took place sufficiently long ago to observe their consequences. They show very small changes in brand offerings relative to the sizes of the firms involved. The case study results are consistent with the absence of noticeable changes in the rate of adding brands to markets, seen in table B.1.

Figure B.2: Small changes in brand offerings following ownership changes




(a) Acquisitions of the two largest Mexican breweries




(b) Diageo and Suntory purchases of Mey Icki and Beam Inc.

# C Endogenous mobility bias: a quantification

Here we investigate the direction and size of bias from assignment processes that depart from equation (27). In particular, we specify an assignment process we call *idiosyncratic sorting* in which brand $b$ is more likely to be assigned to firm $f$ with which they have strong bilateral affinity, denoted $\xi_{bf}$. In the proposed data generating process, $\xi_{bf}$ enters the determination of $\varphi_{bnt}$ and also influences the brand acquisition decision.

The actual assignment process observed in the beer and spirits industries features multi-brand firms acquiring and absorbing other multi-brand firms. We cannot do justice to the complexities of this process here, which we view as the subject for a separate paper. Instead we model a stylized assignment process that captures the key economic principles and their econometric implications. In our DGP, $N$ brands are assigned to $N$ firms in year $t$ based on the value generated by each brand-firm combination:

$$v_{bft} = \varphi_b^B \varphi_f^F \exp(\xi_{bf}) - \Phi_{bft}, \tag{1}$$

where the first term models variable profits as being multiplicative in the brand and firm level determinants of cost-adjusted quality ($\varphi_b^B$ and $\varphi_f^F$) and the idiosyncratic quality of the match ($\xi_{bf}$). The last term, $\Phi_{bft}$ represents the fixed costs incurred by firm $f$ when it produces and sells the products of brand $b$. This term is important for two reasons. First, it is needed to generate mobility of brands across firms over time. Second, it introduces a random component to assignment that has no effect on the observed cost-adjusted appeal. Replacing $\exp(\xi_{bf})$ with its expectation in equation (1) leads to an assignment process that satisfies equation (27). We will refer to this case as *hierarchical sorting* since assignment depends only on the ordering of $\varphi_b^B$ and $\varphi_f^F$ (and chance via the $\Phi_{bft}$ shocks).

Instead of modeling the process of buying and selling brands, we assume that a candidate assignment matrix $\mathbf{\Omega}$ should have the feature that there are no mutually profitable reassignments. We do this by selecting the $\mathbf{\Omega}$ that maximizes industry profits. The equilibrium assignment in each period is the $\Omega_{bft}$ that solves the linear program

$$\text{Maximize} \sum_{f=1}^{N} \sum_{b=1}^{n} v_{bft}\Omega_{bft}, \quad \text{subject to} \quad \sum_{b=1}^{N} \Omega_{bft} = 1, \; \sum_{f=1}^{N} \Omega_{bft} = 1, \; 0 < \Omega_{bft} < 1$$

The first constraint ensures that each brand is assigned to a firm and the second constraint implies that all firms have a brand. The solution to this problem always respects $\Omega_{bft} \in \{0, 1\}$. We solve for a new $\Omega$ matrix in each period $t$, with brands potentially changing owners based on realizations of $\Phi_{bft}$.

To implement this DGP, we set $\varphi^B_b = b$ for $b = 1 \cdots N$, $\varphi^F_f = f$ for $f = 1 \cdots N$, with $N = 100$. The idiosyncratic matching term, $\xi_{bf}$, is distributed Normal(0,1). On average, brands move to firms with whom they have good fit, which implies that $\xi_{bf}$ in the selected sample has an expectation greater than zero. Fixed costs are $\Phi_{bft} \sim$ LogNormal(8,1). The solution of the model repeats for $T$ periods. As $T$ increases, firms connect to each other via brands that have been held in common. Furthermore, within the largest connected set, the connectivity index $\lambda_2$ rises.

Figure C.1: Firm (owner) shares in the variance of brand performance are biased upwards by both limited and endogenous mobility

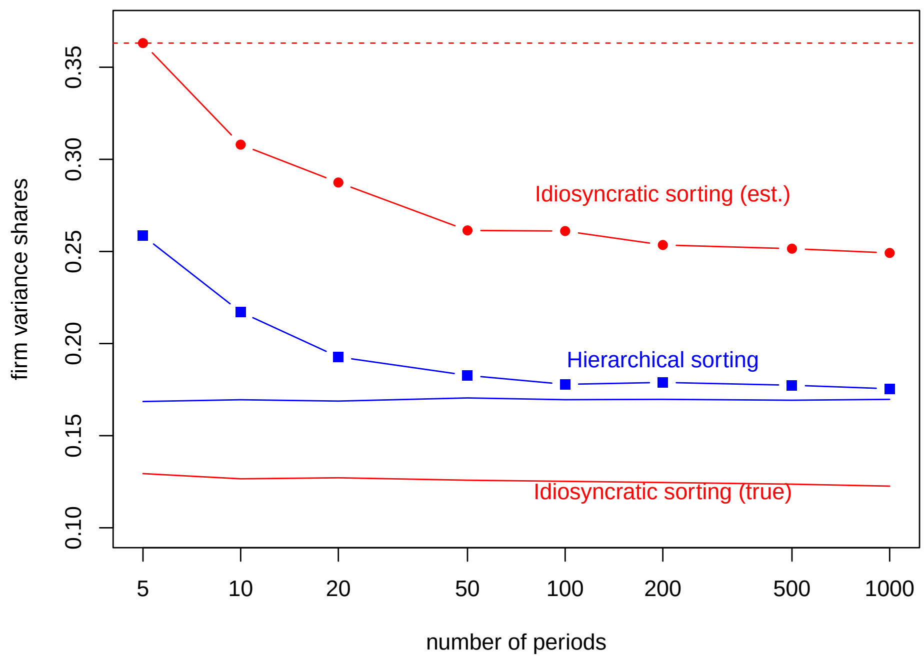



Figure C.1 displays the contribution of the firm (owner) fixed effect ($\varphi^F$) to explaining the variance in $\breve{\varphi}_{bnt}$ in equation 25. The blue lines correspond to a DGP that allows for assortative matching but rules out matching based on $bf$ affinity. We see the familiar limited mobility bias (LMB) result of Andrews et al. (2008) and Bonhomme et al. (2019) that firm shares are overestimated. As mobility increases, the estimated share converges to the true share (which is almost flat because the numerator is not random and the denominator is stable because of the law of large numbers). In contrast, the red lines illustrate endogenous mobility bias (EMB) coupled with LMB. Both biases are upward but only the LMB disappears through increases in the number of periods. One can decompose the total bias into the LMB component—the gap between the last red circle at $T = 1000$ and the horizontal dashed line—and the EMB—the gap between the red circle and the nearly horizontal solid red line.

Figure C.2: The correlation between brand and firm fixed effects is biased downwards, but only due to limited mobility

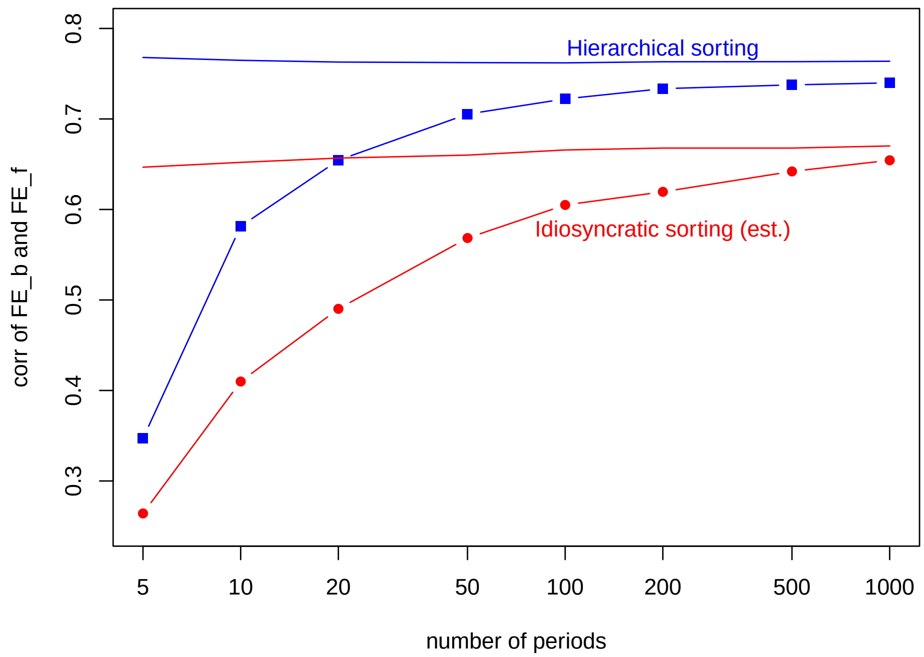
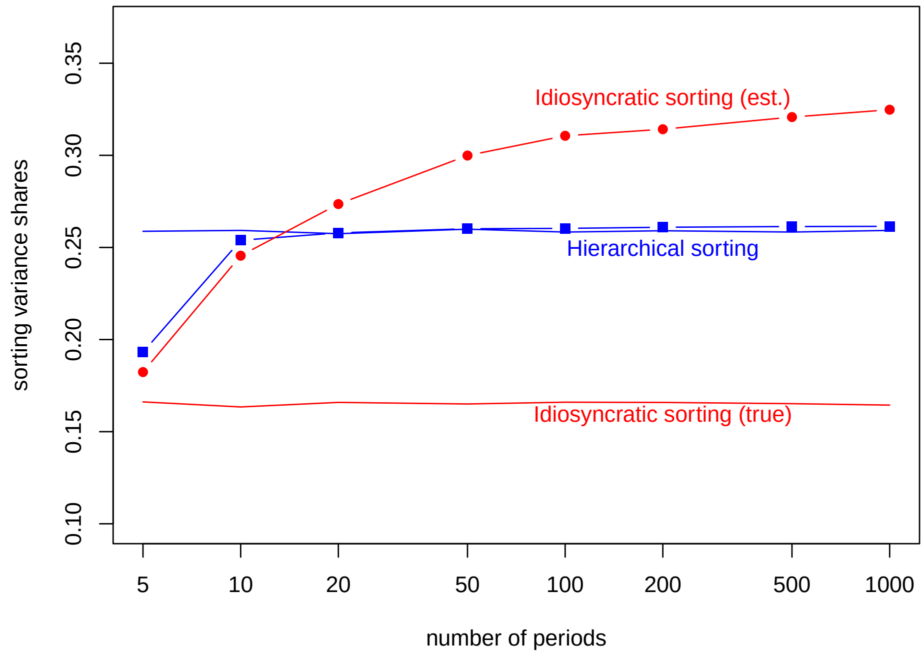



Figure C.2 shows the results from Andrews et al. (2008) and Bonhomme et al. (2023) that correlations between firm and brand fixed effects are biased downwards by limited mobility bias, which disappears for Hierarchical sorting (the AKM assumptions) as the number of periods increase. This is seen in the blue square line converging to the flat solid blue line. Somewhat surprisingly the bias in the correlation also gradually disappears as the number of periods grows for Idiosyncratic sorting that violates the AKM orthogonality condition. However, this requires unrealistically large numbers of periods to eliminate the limited mobility bias. Why is there little or no bias coming purely from endogenous mobility? In figure C.3 we see in the red lines that Idiosyncratic sorting does indeed bias the covariance upwards. So it appears that the lack of bias in the correlations comes from countervailing effects in the numerator and denominator of the correlation formula.

The bottom line we draw from this investigation is that the role of firms in explaining variance in $\varphi_{bn}$ is biased upwards by both limited mobility and endogenous mobility. However, once we take steps in our econometrics of the main text to mitigate limited mobility bias, the estimated firm shares are very small. Hence, bias coming from endogenous mobility should be very small as well. This is corroborated by the event study evidence

Figure C.3: The sorting shares ($2\times$ cov) in the variance of brand performance are biased upwards by endogenous mobility and downwards by limited mobility




in figure 5 and the low explanatory power of the brand-firm interactions.

# D Connectivity of the brand-firm network

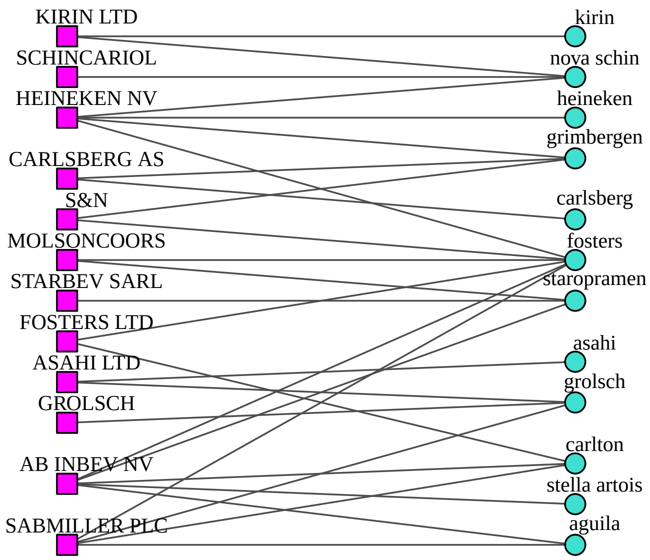
Table D.1: Brand mobility in the largest connected set

| Product group | # Firms | | Mobility | | Sales share | |
|---|---|---|---|---|---|---|
| Beer | 90 | 21 | 13.6 | 50.7 | 80.0 | 70.8 |
| Spirits | 93 | 18 | 8.3 | 32.6 | 57.5 | 42.0 |
| $\geq$ 10 movers | | ✓ | | ✓ | | ✓ |

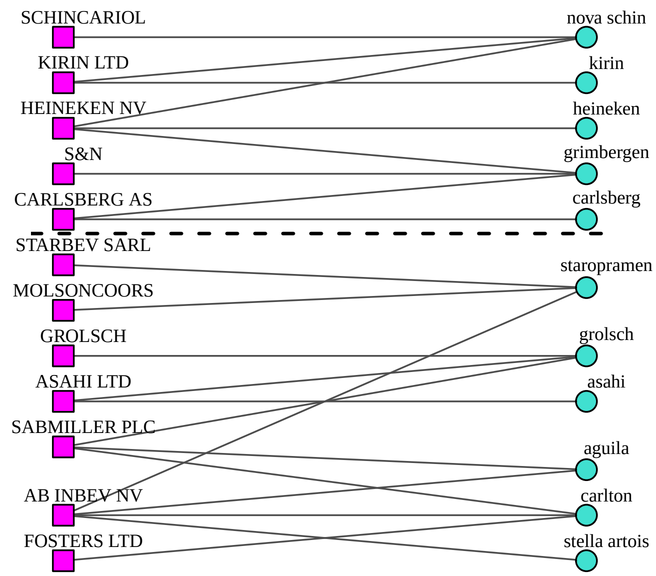
Notes: # Firms is the count of firms in the largest connected set with and without the restriction of 10 or more moving brands per firm. Mobility is the average number of ownership changes per firm in the specified set. Sales share is the set's percentage of world sales.

In the third and fourth columns of Table D.1, we report the mobility ratios for all beverages, showing it for the largest connected set, and within that group, for the firms that experience more than ten movements (the large mobility group). Beer, and to a slightly lesser extent spirits, are characterized by two desirable features in this type of regressions: a high number of ownership changes, combined with a large share of world sales

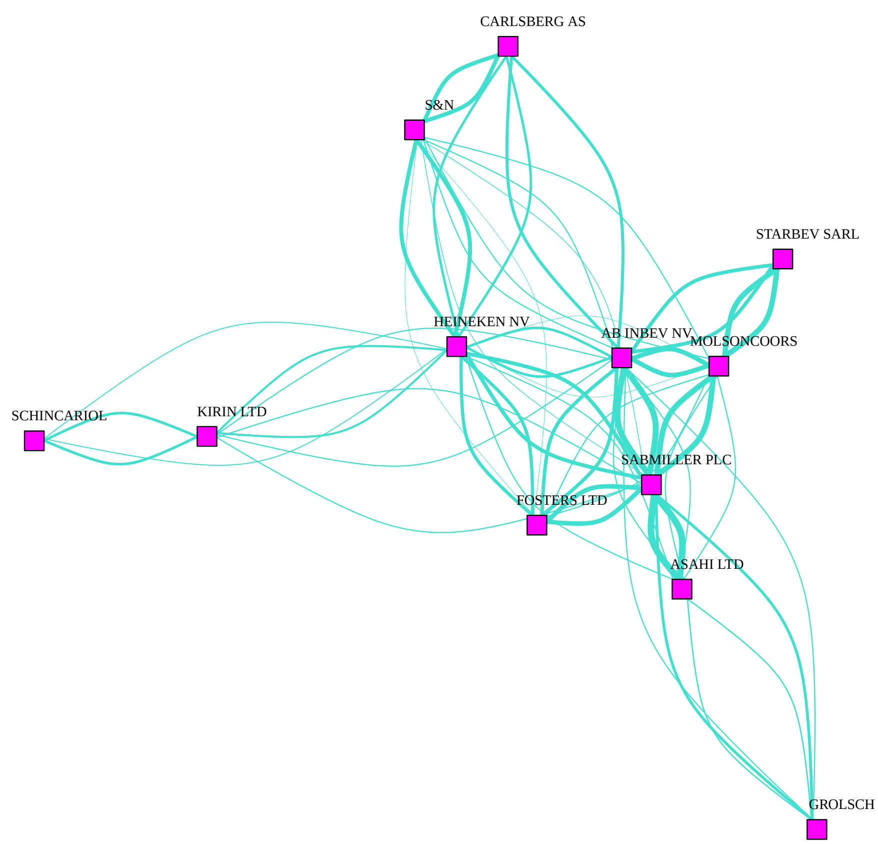
Figure D.4: Visualizing connectivity via an illustrative subset of brands and firms




(a) A connected set of firms and brands




(b) Without the Fosters brand, the sets disconnect




(c) The *induced* firm-to-firm network from panel (a) accounted for by firms in the connected set (shown in columns 5 and 6).

Figure D.4 illustrates the near-disconnectedness problem with an illustrative subset of firms and brands. Without the Fosters brand, the upper section of this graph (Schincariol, Kirin, Scottish & Newcastle, Carlsberg, and Heineken) would detach itself from the rest, as depicted by the dashed line in panel (b). While in this example Fosters is a "bottleneck" brand in the terminology of Kline et al. (2020), in the full dataset it can be removed without disconnecting Carlsberg, Heineken, and Kirin from AB InBev. The KSS leave-one-out set of firms comprises all the major beer makers.

Chung (1997) showed how the eigenvectors of the graph capture whether network is just connected or thickly connected. Jochmans and Weidner (2019) Theorem 2 shows that higher connectivity of the network, measured by $\lambda_2$, shrinks the upper bound for the variance of the estimates of the fixed effects (of firms). In a bipartite network, edges connect two sets of nodes where the only connections are between nodes from different sets. There is an *induced firm-to-firm network* with weighted edges between firms. The edge weight $w(u, v)$ is an increasing function of in-common brand-market-years, with zero weight of a node to itself ($w(u, u) = 0$). The *Laplacian* of the weighted firm-to-firm network is a matrix with $L(u, v) = -w(u, v)$ and $L(u, u) = d_u$, where $d_v = \sum_u w(u, v)$. In the case where $w = 1$, $d_v$ is the degree, that is the number of edges connecting to vertex $v$. The elements of the *normalized* Laplacian are given by $\mathcal{L}(u, v) = -w(u, v)/\sqrt{d_u d_v}$ and $\mathcal{L}(u, u) = 1$. As the smallest eigenvalue of each connected network is always zero, we refer to the smallest *positive* eigenvalue of $\mathcal{L}$ as $\lambda_2$. Chung (1997) shows that the maximum $\lambda_2$ in an unweighted network is $n/(n-1)$, which occurs when each node has an edge to every other node. As the number of nodes grows large, $\lambda_2 \to 1$.

For all $u \neq v$, Jochmans and Weidner (2019) specify the weights as

$$w(u, v) = \sum_b \frac{n_{ub} n_{vb}}{N_b},$$

where $n_{ub}$ is the count of market-years where brand $b$ belongs to firm $u$ and

$$n_{ub} = \sum_{nt} 1_{b \in \mathcal{F}_u} \times 1_{s_{bnt} > 0},$$

and $N_b$ is the brand's total market-years under all owners:

$$N_b = \sum_f n_{fb}.$$

Figure D.4(c) shows the induced network of firm-to-firm links where the turquoise edges are based on brand-market-years. The thickness of these lines is proportional to the log of the Jochmans and Weidner (2019) weights described above. In this panel, *all* the brands are used in the weight calculation, not just the 12 illustrative brands in panel (a).

# E Additional regression results

Table E.1: Pooled beer + spirits regressions, without firm fixed effects

| | | | Bertrand | Cournot |
|---|---|---|---|---|
| | $\ln s_{bn}$ | $\ln A_{bn}$ | $\ln \varphi_{bn}$ | $\ln \varphi_{bn}$ |
| home | $1.148^{a}$ | $0.168^{a}$ | $0.309^{a}$ | $0.323^{a}$ |
| | (0.124) | (0.051) | (0.033) | (0.034) |
| distance | $-0.247^{a}$ | $-0.035^{c}$ | $-0.062^{a}$ | $-0.063^{a}$ |
| | (0.042) | (0.019) | (0.011) | (0.011) |
| common language | $0.212^{b}$ | 0.029 | $0.056^{b}$ | $0.057^{a}$ |
| | (0.085) | (0.038) | (0.022) | (0.022) |
| home (HQ) | $0.294^{a}$ | $0.073^{b}$ | $0.088^{a}$ | $0.096^{a}$ |
| | (0.099) | (0.037) | (0.026) | (0.027) |
| distance (HQ) | 0.035 | $0.021^{c}$ | 0.008 | 0.007 |
| | (0.029) | (0.011) | (0.007) | (0.008) |
| com. lang. (HQ) | 0.092 | 0.002 | 0.023 | 0.024 |
| | (0.060) | (0.024) | (0.016) | (0.017) |
| Observations | 95,399 | 95,399 | 95,399 | 95,399 |
| $R^2$ | 0.813 | 0.719 | 0.649 | 0.653 |

Notes: Standard errors in (), clustered by origin-market dyads. Fixed effects at the brand-product and market-year-product dimensions included in each specification. HQ variables defined with respect to brand owner's headquarters country. Significance levels: 1% ($a$), 5% ($b$), and 10% ($c$).

Table E.2: Pooled beer + spirits regressions within the largest connected set

| | | | Bertrand | Cournot |
|---|---|---|---|---|
| | $\ln s_{bn}$ | $\ln A_{bn}$ | $\ln \varphi_{bn}$ | $\ln \varphi_{bn}$ |
| home | $1.222^{a}$ | $0.201^{a}$ | $0.326^{a}$ | $0.338^{a}$ |
| | (0.150) | (0.057) | (0.040) | (0.041) |
| distance | $-0.226^{a}$ | $-0.021$ | $-0.057^{a}$ | $-0.058^{a}$ |
| | (0.047) | (0.020) | (0.012) | (0.013) |
| common language | $0.215^{b}$ | 0.031 | $0.056^{b}$ | $0.058^{b}$ |
| | (0.095) | (0.043) | (0.025) | (0.025) |
| home (HQ) | $0.264^{b}$ | 0.047 | $0.094^{a}$ | $0.110^{a}$ |
| | (0.133) | (0.048) | (0.035) | (0.035) |
| distance (HQ) | 0.057 | $0.024^{c}$ | 0.015 | 0.014 |
| | (0.039) | (0.015) | (0.010) | (0.010) |
| com. lang. (HQ) | 0.114 | 0.005 | 0.031 | $0.034^{c}$ |
| | (0.072) | (0.029) | (0.020) | (0.020) |
| Observations | 65,097 | 65,097 | 65,097 | 65,097 |
| $R^2$ | 0.790 | 0.675 | 0.611 | 0.615 |

Notes: The sample is restricted to the largest connected set, within a product category. Standard errors in (), clustered by origin-market dyads. Fixed effects at the brand-product, firm, and market-year-product dimensions included in each specification. HQ variables defined with respect to brand owner's headquarters country. Significance levels: 1% ($a$), 5% ($b$), and 10% ($c$).

## E.1 Correlations of brand and firm fixed effects, with low mobility bias

Here we show the full set of correlation and variance shares for the fixed effects obtained in four different regressions using market shares, appeal, and cost-adjusted appeal (calculated under both conduct assumptions) as the dependent variables.

Table E.3 shows fixed effect correlations for regressions on all firms in the largest connected set. The underlying regressions in table E.4 apply the AGSU restrictions (keeping only moving brands and high mobility firms) to the estimating sample. In each table, the diagonal shows the ratio of the variance of the relevant fixed effect to the variance of the dependent variable. The off-diagonal elements of Table E.4 show the sign and magnitude of assortative matching.

Table E.3: Correlations between fixed effects in the largest connected set

| | Brand | | | | Firm | | | |
|---|---|---|---|---|---|---|---|---|
| Dep. var.: | share ($s_{bn}$) | appeal ($A_{bn}$) | type B ($\varphi_{bn}$) | type C ($\varphi_{bn}$) | share ($s_{bn}$) | appeal ($A_{bn}$) | type B ($\varphi_{bn}$) | type C ($\varphi_{bn}$) |
| **Beer** | | | | | | | | |
| brand market share | 0.903 | | | | | | | |
| brand appeal | 0.733 | 0.914 | | | | | | |
| brand type B | 0.993 | 0.713 | 0.894 | | | | | |
| brand type C | 0.989 | 0.706 | 0.999 | 0.883 | | | | |
| firm market share | -0.306 | -0.210 | -0.303 | -0.297 | 0.111 | | | |
| firm appeal | -0.254 | -0.312 | -0.243 | -0.238 | 0.785 | 0.174 | | |
| firm type B | -0.290 | -0.194 | -0.292 | -0.286 | 0.986 | 0.760 | 0.110 | |
| firm type C | -0.277 | -0.183 | -0.280 | -0.275 | 0.974 | 0.748 | 0.996 | 0.107 |
| **Spirits** | | | | | | | | |
| brand market share | 0.890 | | | | | | | |
| brand appeal | 0.686 | 0.867 | | | | | | |
| brand type B | 0.998 | 0.685 | 0.889 | | | | | |
| brand type C | 0.996 | 0.684 | 1.000 | 0.886 | | | | |
| firm market share | -0.455 | -0.237 | -0.451 | -0.452 | 0.357 | | | |
| firm appeal | -0.375 | -0.371 | -0.376 | -0.377 | 0.760 | 0.228 | | |
| firm type B | -0.452 | -0.238 | -0.450 | -0.451 | 0.996 | 0.762 | 0.365 | |
| firm type C | -0.450 | -0.237 | -0.448 | -0.449 | 0.993 | 0.763 | 0.999 | 0.373 |

Notes: For brand and firm type, we use B and C to denote Bertrand and Cournot conduct, respectively. **Diagonal:** ratio of FE variances to variance of the dependent variable. **Off-diagonal:** correlation. Underlying regressions keep the largest connected set.

As found in AGSU, the patterns of correlation in the largest connected set exhibit *negative* assortative matching: all correlations between brands and firm fixed effects are negative and large in absolute value, for both beer and spirits. After imposing the AGSU

Table E.4: Correlations between fixed effects in the AGSU restricted sample

| | Brand | | | | Firm | | | |
|---|---|---|---|---|---|---|---|---|
| Dep. var.: | share ($s_{bn}$) | appeal ($A_{bn}$) | type B ($\varphi_{bn}$) | type C ($\varphi_{bn}$) | share ($s_{bn}$) | appeal ($A_{bn}$) | type B ($\varphi_{bn}$) | type C ($\varphi_{bn}$) |
| **Beer** | | | | | | | | |
| brand market share | 0.831 | | | | | | | |
| brand appeal | 0.796 | 0.872 | | | | | | |
| brand type B | 0.994 | 0.788 | 0.824 | | | | | |
| brand type C | 0.989 | 0.783 | 0.999 | 0.820 | | | | |
| firm market share | -0.131 | -0.155 | -0.130 | -0.132 | 0.045 | | | |
| firm appeal | -0.106 | -0.175 | -0.106 | -0.108 | 0.902 | 0.088 | | |
| firm type B | -0.114 | -0.132 | -0.115 | -0.117 | 0.985 | 0.884 | 0.042 | |
| firm type C | -0.103 | -0.118 | -0.105 | -0.107 | 0.966 | 0.866 | 0.995 | 0.042 |
| **Spirits** | | | | | | | | |
| brand market share | 0.843 | | | | | | | |
| brand appeal | 0.720 | 0.836 | | | | | | |
| brand type B | 0.998 | 0.726 | 0.845 | | | | | |
| brand type C | 0.996 | 0.727 | 1.000 | 0.849 | | | | |
| firm market share | -0.245 | -0.175 | -0.241 | -0.240 | 0.085 | | | |
| firm appeal | -0.111 | -0.121 | -0.116 | -0.119 | 0.631 | 0.039 | | |
| firm type B | -0.255 | -0.183 | -0.253 | -0.252 | 0.995 | 0.636 | 0.096 | |
| firm type C | -0.266 | -0.188 | -0.264 | -0.264 | 0.988 | 0.636 | 0.998 | 0.106 |

Notes: For brand and firm type, we use B and C to denote Bertrand and Cournot conduct, respectively. **Diagonal:** ratio of FE variances to variance of the dependent variable. **Off-diagonal:** correlation between fixed effects from regressions on samples limited to the largest connected set, brands that changed ownership, and firms with 10+ moving brands.

restrictions in Table E.4, the correlations become much smaller, and not even systematically negative for spirits. Firm effects under the AGSU restrictions explain just a small part of the variance of performance measures for both beer and spirits. Therefore, the identity of the firm owning a brand explains relatively little of the variance in its market share, appeal and cost-adjusted appeal. Brand effects explain a much larger share of the overall variance. It is possible, in the presence of negative covariance between firm and brand fixed effects, for brand effects to explain more than 100% of the overall performance. We see this for beer in Table E.4.

Table E.5: The explanatory power of owner fixed effects: Cournot conduct

| Type of FE | # of FE | $\lambda_2$ | $\Delta R^2$ | Varshr | FE Corr |
|---|---|---|---|---|---|
| | | **Beer** | | | |
| Firms (All) | 464 | 0.000 | 0.005 | NA | NA |
| Firms (Largest connected set, AKM) | 90 | 0.013 | 0.005 | 0.107 | -0.275 |
| Firms (Leave-out-match, KSS) | 50 | 0.072 | 0.004 | 0.085 | -0.255 |
| Firms (High mobility, AGSU) | 22 | 0.169 | 0.004 | 0.042 | -0.107 |
| Clusters (BLM) | 15 | 0.537 | 0.001 | 0.010 | 0.179 |
| Clusters (BLM) | 10 | 0.748 | 0.001 | 0.009 | 0.138 |
| Clusters (BLM) | 5 | 0.958 | 0.000 | 0.003 | 0.196 |
| | | **Spirits** | | | |
| Firms (All) | 850 | 0.000 | 0.008 | NA | NA |
| Firms (Largest connected set, AKM) | 93 | 0.012 | 0.009 | 0.373 | -0.449 |
| Firms (Leave-out-match, KSS) | 43 | 0.015 | 0.004 | 0.233 | -0.355 |
| Firms (High mobility, AGSU) | 19 | 0.071 | 0.006 | 0.106 | -0.264 |
| Clusters (BLM) | 15 | 0.345 | 0.001 | 0.026 | 0.075 |
| Clusters (BLM) | 10 | 0.603 | 0.001 | 0.011 | 0.131 |
| Clusters (BLM) | 5 | 0.870 | 0.000 | 0.005 | 0.273 |

Notes: # of FE is either number of firms or clusters. $\lambda_2$ measures network connectivity. $\Delta R^2$ is the difference in $R^2$ between the full specification and one excluding firm/cluster fixed effects. Varshr is the ratio of the variance of firm/cluster FEs to the variance of brand type ($\ln \varphi_{bn}$, conduct =Cournot). FE corr is the correlation between brand and firm/cluster FEs.

Table E.6: Friction estimates, alternative heterogeneity assumptions: Cournot conduct

| | Beer | | | Spirits | | |
|---|---|---|---|---|---|---|
| Fixed effects: | $b+f$ | $b+k$ | $bf$ | $b+f$ | $b+k$ | $bf$ |
| home | $0.465^a$ | $0.478^a$ | $0.475^a$ | $0.178^a$ | $0.172^a$ | $0.178^a$ |
| | (0.051) | (0.049) | (0.051) | (0.043) | (0.042) | (0.044) |
| distance | $-0.051^a$ | $-0.054^a$ | $-0.058^a$ | $-0.064^a$ | $-0.061^a$ | $-0.064^a$ |
| | (0.018) | (0.016) | (0.018) | (0.015) | (0.015) | (0.015) |
| common language | $0.096^b$ | $0.100^b$ | $0.094^b$ | 0.032 | 0.035 | 0.035 |
| | (0.041) | (0.040) | (0.042) | (0.026) | (0.025) | (0.026) |
| home (HQ) | $0.102^c$ | 0.068 | 0.091 | $0.141^a$ | $0.131^a$ | $0.154^a$ |
| | (0.055) | (0.043) | (0.059) | (0.039) | (0.035) | (0.041) |
| distance (HQ) | $-0.037^b$ | $-0.027^a$ | $-0.037^b$ | $0.031^a$ | $0.026^a$ | $0.035^a$ |
| | (0.015) | (0.010) | (0.019) | (0.011) | (0.010) | (0.012) |
| com. lang. (HQ) | −0.034 | −0.035 | −0.030 | $0.052^a$ | $0.044^b$ | $0.052^b$ |
| | (0.035) | (0.032) | (0.038) | (0.020) | (0.019) | (0.021) |
| Observations | 34,724 | 34,724 | 34,724 | 60,675 | 60,675 | 60,675 |
| $R^2$ | 0.737 | 0.733 | 0.752 | 0.606 | 0.599 | 0.611 |
| RMSE | 0.206 | 0.206 | 0.201 | 0.208 | 0.208 | 0.206 |

Notes: Standard errors in (), clustered by origin-market dyads. Dependent variable: $\ln \varphi_{bn}$. Market-year-product fixed effects in each regression. HQ variables determined by brand owner's headquarters country. Significance levels: 1% ($a$), 5% ($b$), and 10% ($c$).

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