Appendix for 'How much do consumers care about new and discontinued products? A case study of the MillerCoors merger'*

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Abstract

This paper finds evidence of product variety changes due to a merger and compares the welfare effects of these changes with those of price changes in the context of the MillerCoors merger of 2008. I first test whether the merger had any effect on product variety directly. I find that the merged firm decreased the number of brands offered and offset this by increasing product variety in more successful brands. However, under a difference-and-differences framework, I find that product variety declined relative to that of other top competitors. I then use a random coefficient nested logit model and estimate demand for the MillerCoors merger in the postmerger period, expanding on work from Miller and Weinberg (2017). In a set of two counterfactuals, I test the value of new products created after the merger and the value of discontinued products lost after the merger. I find that the merger increased consumer surplus from changes in product variety: consumer surplus increased by 1.25% from new products created and decreased by 0.14% from the loss of discontinued products after the merger. Benchmarking this to results in the literature, I find that the effects of product addition and discontinuation are approximately 34% and -4%, respectively, of the consumer welfare effects of the postmerger price changes in the presence of coordinated pricing found in prior work.

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1 Data Cleaning and Summaries

This project uses a variety of datasets to fully understand the effect of the MillerCoors merger on product variety. As such, this data appendix contains information on each dataset and what is done to clean the data. Each section describes the dataset, provides summary statistics, and describes the data cleaning process and justification for any changes made. The final section describes how merges between datasets were accomplished.

1.1 The IRI Marketing Data Set

The first data source is the IRI Marketing Supermarket data set. The IRI Marketing data set spans from 2001 - 2012 and contains supermarket transaction data from 51 marketing regions. These marketing regions are either singular counties or groups of counties. Each observation is an individual sale of a product with a unique UPC. The sale recorded is the total price of the sale, the number of units of that good purchased, which store (anonymized by year) it was purchased in and which market it was purchased in. Each good is further identified on their brand, vendor, parent company, packaging medium, and the size by ounces.

Due to the size of the data, the data is split into four different groups of files per year. The first group contains the individual sales of each beer as described above. The second group are product information files. There are four of these files: One for 2001 - 2006, one for 2007, one for 2008 - 2011 and one for 2012. For each file, IRI provides product information for each brand within the time frame listed. However, any changes to any brand during this period is overwritten - for example, if a brand were to change parent companies over the course of a year, this would not be observed in the dataset. The third group are the dates files and lists the week that the product was purchased. Using this, I am able to tell which week, month and year the item was purchased in. I use the start of the week to determine what year or month it is in. For years where the first week falls within a different year, I attribute the week to January of the current year. The fourth group is the delivery files, which list the market and anonymized stores where sales were conducted. There is one duplicate store chain, which I remove the earliest version of.

For the purposes of this project I remove several markets and a year of data that are problematic for either estimation or data reasons. First, there were several major store level mergers that occurred in 2001. To solely focus on the MillerCoors merger, data from the year 2001 are dropped. To remove potential external constraints on product variety, I do not include markets from states that place restrictions on alcohol varieties (such as limits on ABV) or distribution. These states include Pennsylvania, Kansas, Utah, Oklahoma and Minnesota. I remove Harrisburg, Philadelphia, Tulsa, Oklahoma City, Salt Lake City, and Minneapolis. I remove Providence, Rhode Island since it drops out of the dataset in 2007. Finally, I remove state level markets so census controls on individual markets can be better utilized. This includes Mississippi and South Carolina. This reduces the number of markets in this study to 39 markets in a total of 28 states.

1.1.1 Algorithm to clean the IRI dataset

The algorithm to clean the IRI data and prepare it for analysis proceeds as follows: each year, all IRI data for the year is merged together, new variables are generated, then I calculate summary statistics by month and year and output them for later analysis. There are three variants of this algorithm that create summary statistics for the following categories: the entire dataset, for each market and for each firm. Each one uses the following algorithm for merging:

1. I read in the scanner data and drop products that are missing units.
2. I merge the product information to the scanner data.
3. I read in store and market data. I drop stores that are duplicated or have other issues as described in the last section.
4. I drop all markets that have issues, as described in the last section.
5. I combine the data with the dates data to get the exact weeks the products were sold.
6. I attribute any week ending in January to January, and drop data from weeks ending in January of next year.
7. I merge with the file that identifies which products belong to Miller and Coors prior to the merger and which do not.
8. Using the above classification, I identify if goods are from Miller, from Coors, from MillerCoors, and whether they were new MillerCoors goods.
9. I calculate market shares and HHI at the national level and at the market level per year and per month.
10. I calculate summary statistics for the categories described above for month and year. I repeat this process for Miller classified goods only, Coors classified goods only and MillerCoors classified goods only.
11. For certain subsets of the data, I calculate the change in brands and the change in products over time. This is done through getting the list of brands, cleaning both to address any minor text changes (Such as Hamms and Hamm's), and then merging both to find which brands matched (continued), which brands do not match in the latest data (discontinued) and which brands do not match from earlier data (new). I do this for both products and brands. Additional cleaning is done to remove brands that are discontinued twice from the discontinued category and brands that are considered new twice from the new category.
12. The data is saved then used for summary statistics within the paper.

1.1.2 Categorizing Brands in the IRI dataset

During the period of study, brands may change either their vendor or parent company due to mergers, acquisitions or spinoff subsidiaries. In the results presented in the paper, I use Brand-Parent to categorize goods. For Miller and Coors brands, I use Brand-Parent to categorize goods for each company prior to the merger, and track which goods are still available after the merger. I use Brand-Parent primarily to include subsidiary companies. Subsidiary companies could be a target for the merger, and therefore their product variety may be affected by a merger.

1.2 Examining features of the Discontinued and New Brands

I provide graphs summarizing features of new and discontinued brands below. The features I examine are revenues of new and discontinued brands in their first and last year respectively, the total products under each brand, the total products sold under each brand, the market share of new and discontinued brands in their first and last year respectively, the share that new and discontinued brands contributed to the parent company's market share, the mean number of markets and the mean number of stores.

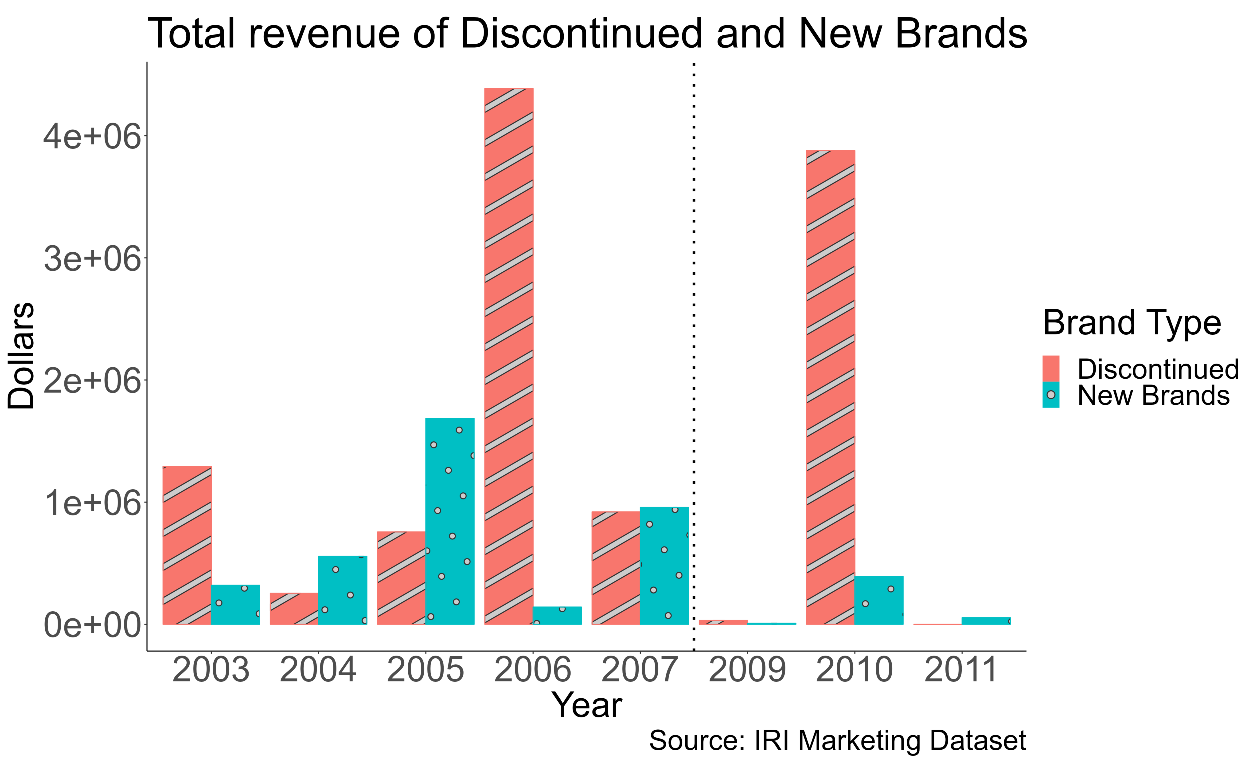


Figure 1: This graph shows information from brands that were added in that year and brands that were discontinued after that year. 2008 is removed due to data issues. Prior to 2009, "new brands" and "discontinued brands" are the sum of the Coors and Miller new and discontinued brands, respectively. From 2009 onward, the "new brands" and "discontinued brands" are for MillerCoors only.

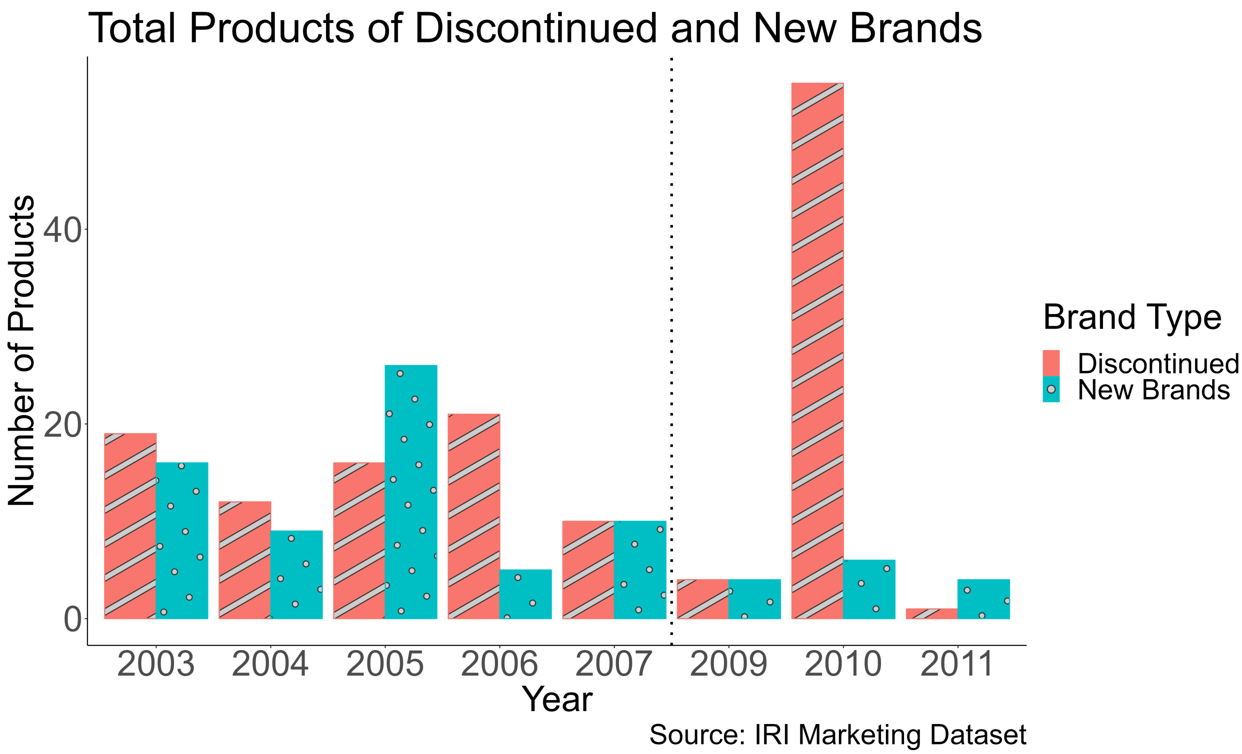


Figure 2: This graph shows information from brands that were added in that year and brands that were discontinued after that year. 2008 is removed due to data issues. Prior to 2009, "new brands" and "discontinued brands" are the sum of the Coors and Miller new and discontinued brands, respectively. From 2009 onward, the "new brands" and "discontinued brands" are for MillerCoors only.

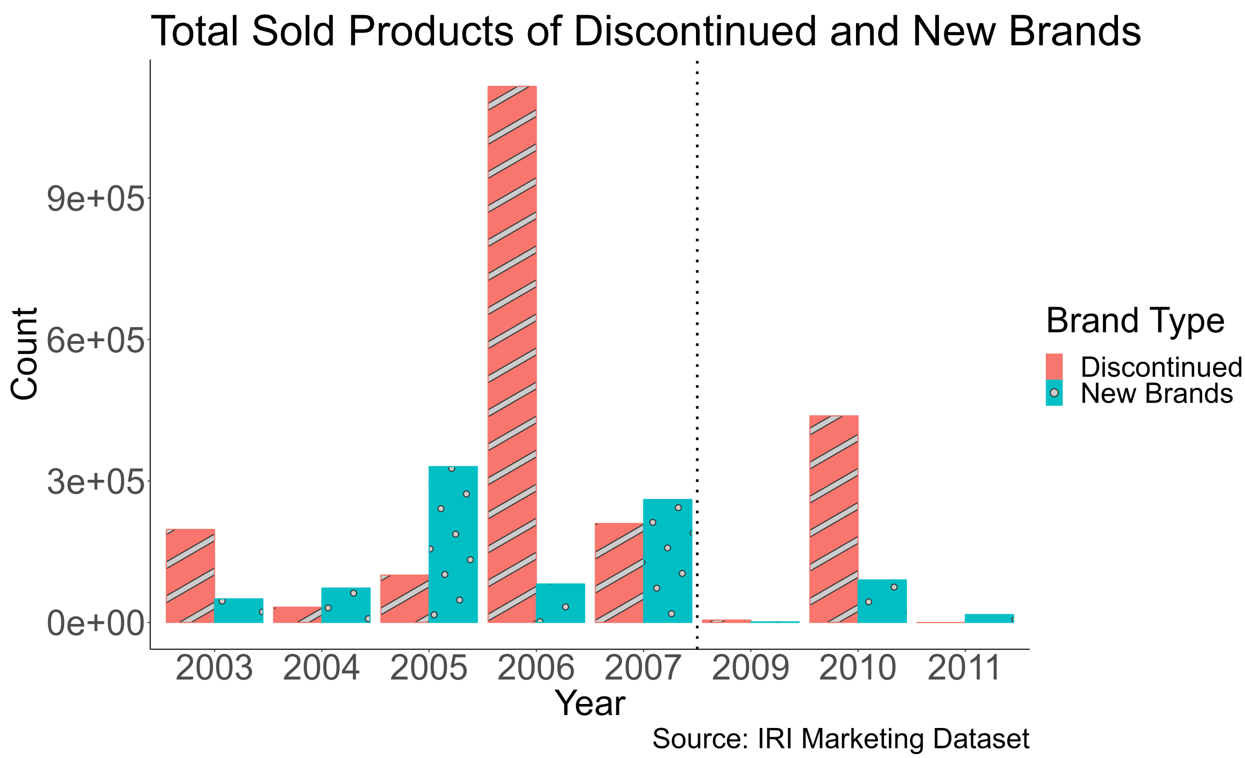


Figure 3: This graph shows information from brands that were added in that year and brands that were discontinued after that year. 2008 is removed due to data issues. Prior to 2009, "new brands" and "discontinued brands" are the sum of the Coors and Miller new and discontinued brands, respectively. From 2009 onward, the "new brands" and "discontinued brands" are for MillerCoors only.

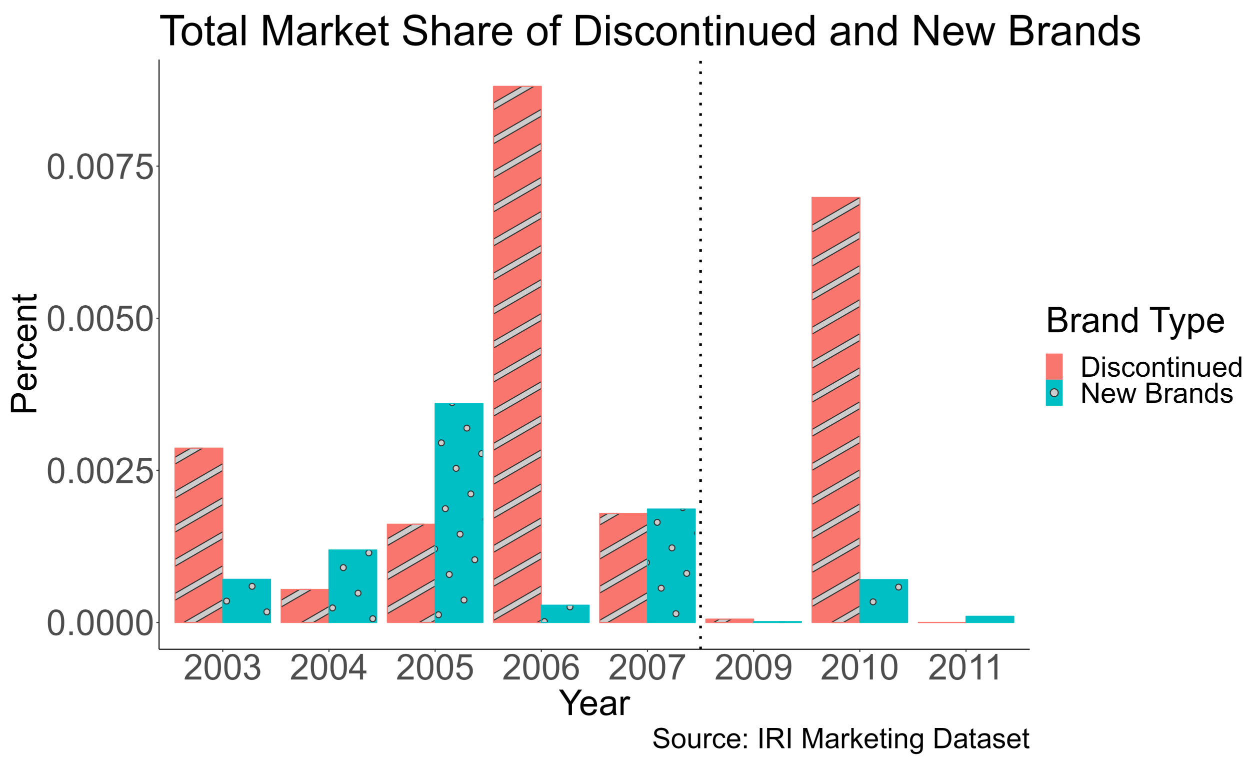


Figure 4: This graph shows information from brands that were added in that year and brands that were discontinued after that year. 2008 is removed due to data issues. Prior to 2009, "new brands" and "discontinued brands" are the sum of the Coors and Miller new and discontinued brands, respectively. From 2009 onward, the "new brands" and "discontinued brands" are for MillerCoors only.

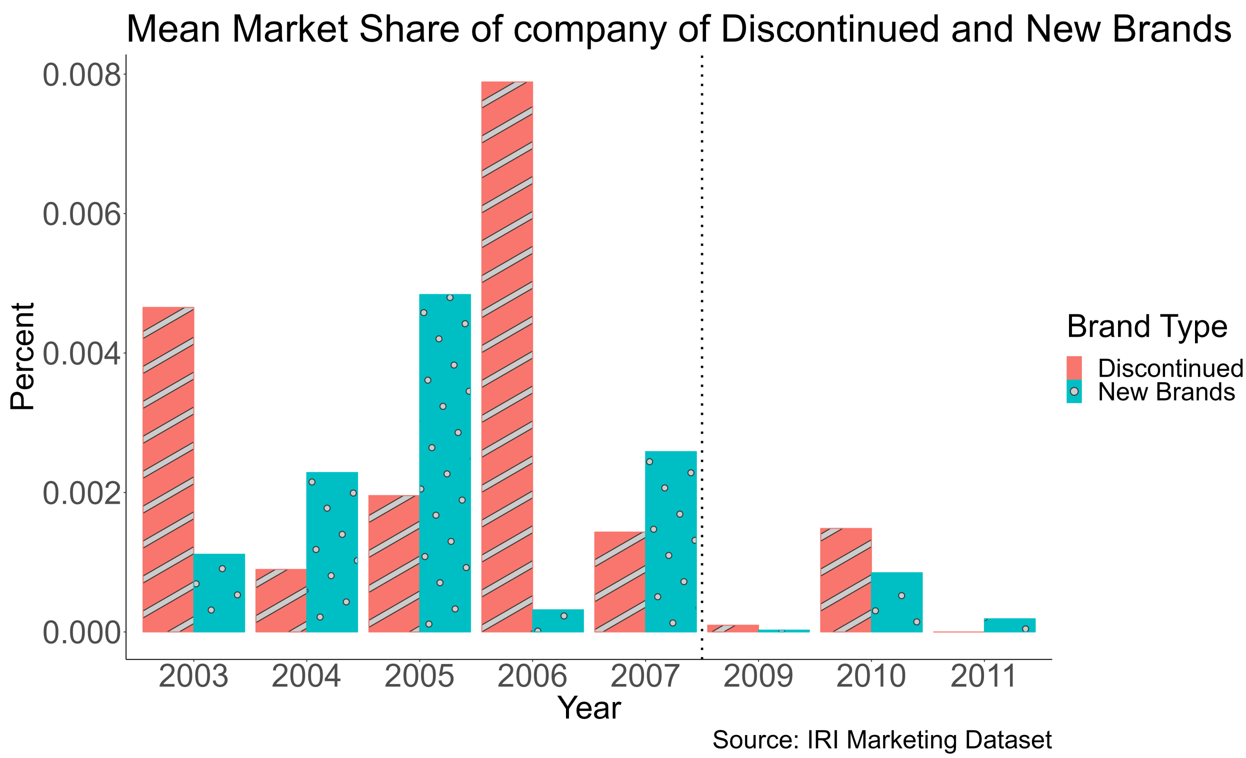


Figure 5: This graph shows information from brands that were added in that year and brands that were discontinued after that year. 2008 is removed due to data issues. Prior to 2009, "new brands" and "discontinued brands" are the sum of the Coors and Miller new and discontinued brands, respectively. From 2009 onward, the "new brands" and "discontinued brands" are for MillerCoors only.

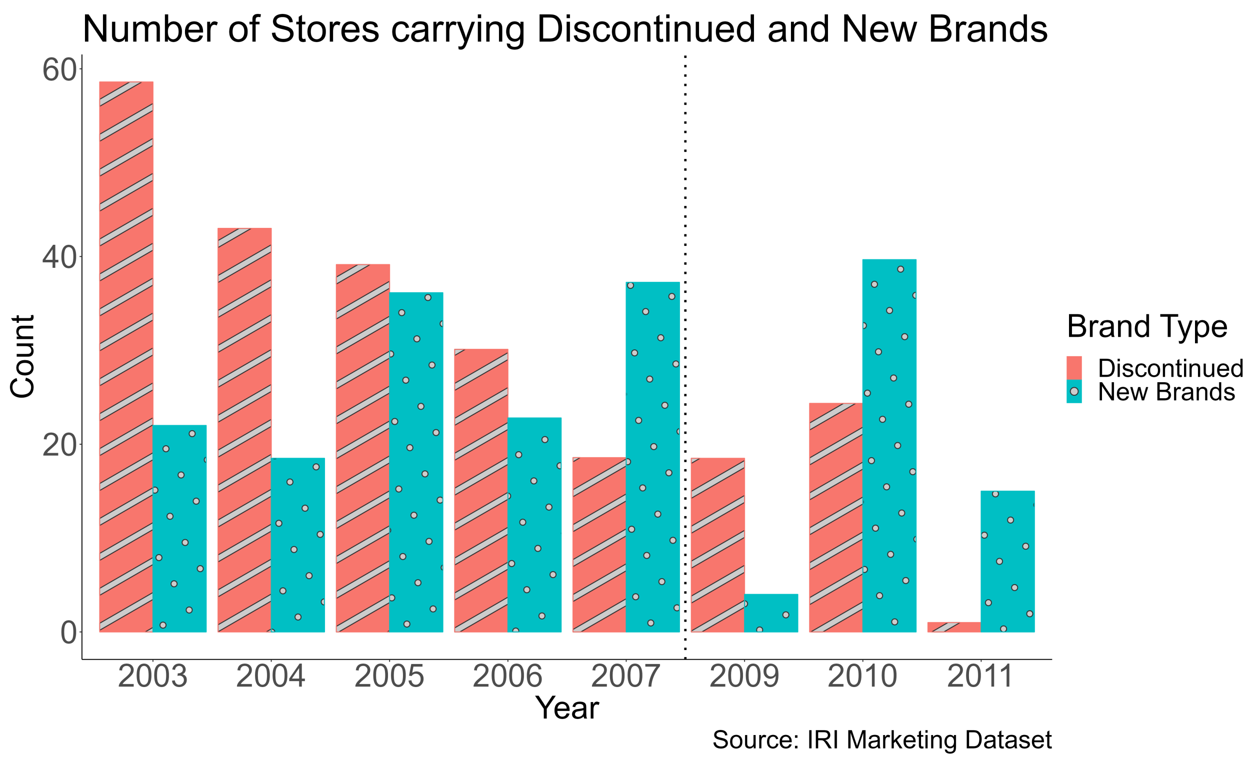


Figure 6: This graph shows information from brands that were added in that year and brands that were discontinued after that year. 2008 is removed due to data issues. Prior to 2009, "new brands" and "discontinued brands" are the sum of the Coors and Miller new and discontinued brands, respectively. From 2009 onward, the "new brands" and "discontinued brands" are for MillerCoors only.

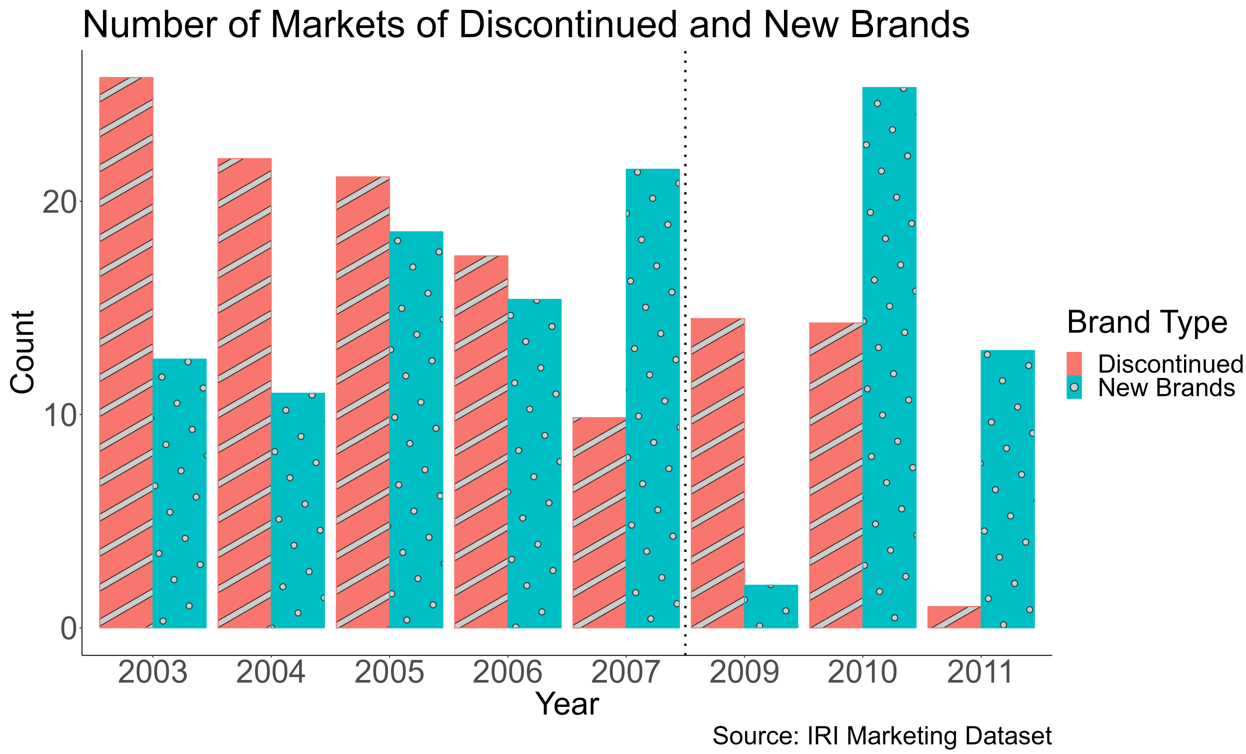


Figure 7: This graph shows information from brands that were added in that year and brands that were discontinued after that year. 2008 is removed due to data issues. Prior to 2009, "new brands" and "discontinued brands" are the sum of the Coors and Miller new and discontinued brands, respectively. From 2009 onward, the "new brands" and "discontinued brands" are for MillerCoors only.

Overall, the data appears to be quite noisy prior to the merger but levels out for the most part after the merger. Notable trends from these figures are the changes in revenue, market share and sold products right before the merger, and the trend in market share after the merger. First, there were major declines prior to the merger in the number of sold products, but products introduced in that year made enough revenue to offset those losses, and similarly market share was high enough to offset the losses. However, after the merger, in 2010 and 2011, the discontinued products had more market share and more lost revenue than new products at the time. These trends are similar to the trends in new and discontinued brands in the paper with a slight decline after the merger leading to an increase in the last year.

Finally, these are not major products. This can be shown in the Mean Market Share Figure, which shows the share that new and discontinued products contribute to the firm's overall market share. At most, the new products contribute to 0.5% of their company's market share, and the discontinued products contribute to 0.3% of their company's market share.

1.3 The Beverage Marketing Corporation Brewery and Importer Database

The Beverage Marketing Corporation Brewery Database contains information on 554 select brewery Locations from 2006 to 2010. This dataset includes information on company names, location, key personnel, capacity, employment, location they serve, manufacturing lines, and what brands they produce at each brewery. This data can be linked to the the IRI dataset via Parent Company. Since multiple breweries make one brand, it is difficult to link the data to one brewery without making assumptions on what brewery makes what specific product shipped to the store.

Additionally, there is an importer supplement of the data that contains limited information on importers and imported brands. One key issue is that the importer data includes wine and liquor importers, with limited data on beer importers. Due to this constraint, I limit the importer data to only parent companies in the top 5 percentile of market share, as those can be clearly defined and located in the data. Other import beers are either not included in the IRI data or difficult to link due to brand name uncertainty. Importer data does not contain information on where capacity and the importer's home country, but does contain all other variables in the brewery database. I again chose the midpoint and topcodes for variables that only provided data in ranges.

For data cleaning, one important clarification is that the employment and capacity data is given in ranges and is topcoded. Due to this, I choose the midpoint of these ranges for summary statistics and estimation, and choose the value the data is topcoded at for topcodes. Table 1 shows the summary statistics for Capacity, Employment and Location for All breweries and Miller and Coors breweries and importers. Table 2 aggregates the breweries together at the parent company level to show summary statistics for total employment, capacity, brands and manufacturing lines.

1.4 How Miller and Coors breweries compare to other breweries

Here I provide distributions of the summary statistic variables above and examine how Miller and Coors compare to other breweries in the dataset. These include employment, capital factors, and location of these breweries. Overall, I find that Miller and Coors were large breweries with large amounts of capital and labor, but lacked regional coverage. This provides evidence into the descriptive reasons for the merger as described in the paper.

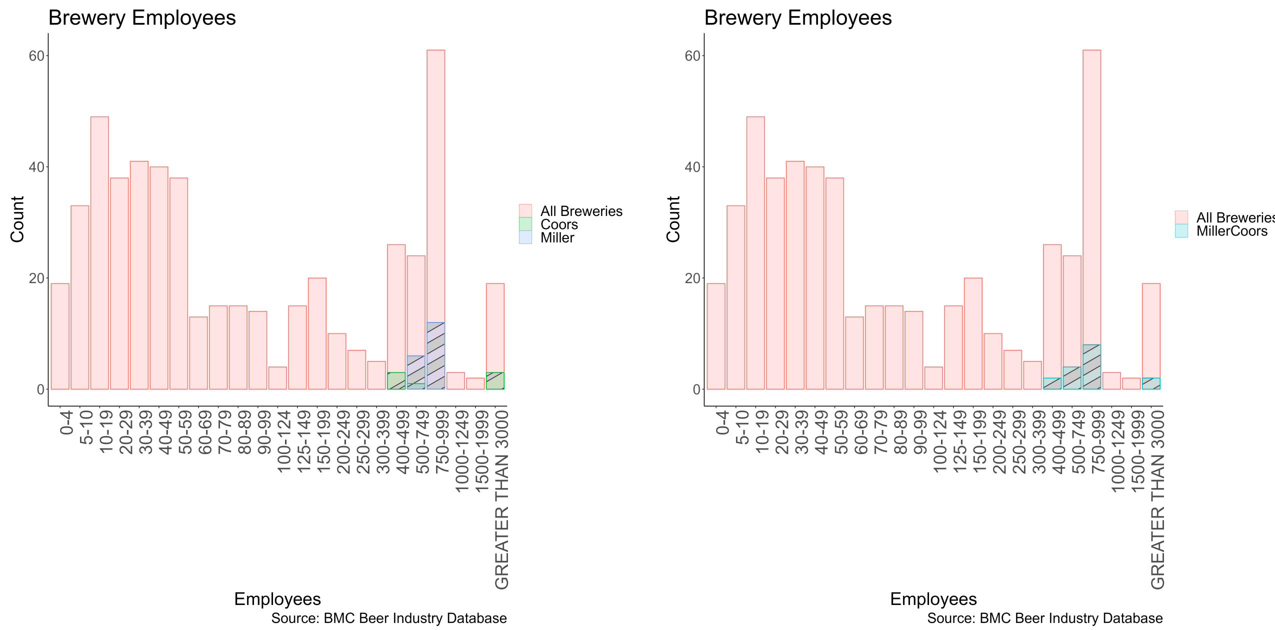
Figure 8 shows the total employment for Miller and Coors before and after the merger, compared to its competitors. Overall, employment was on the higher end, yet slightly decreased due to the loss of the Tennessee Plant prior to the merger. There does not seem to be any other change in employment before and after the merger for Miller and Coors. Employment remained in the upper distribution of employment at most plants.

Table 1: Summary Statistics, Individual Brewery Level

	Count			
Number of Unique Breweries	130			
Number of Unique Breweries, Coors	3			
Number of Unique Breweries, Miller	6			
Number of Firms in the top 5% percentile that sell imports	8			
Share of Firms in the top 5% percentile that sell imports and domestic brands	40%			
	Mean	Standard Deviation	Minimum	Maximum
Capacity, All Breweries	2425783.16	4230236.58	499.5	20000000
Capacity, Coors	11714285.43	7750576.28	5499999.5	20000000
Capacity, Miller	8166666.17	970142.50	6499999.5	9499999.5
Employment, All Breweries	327.86	611.13	2	3000
Employment, Coors	1567.57	1341.34	449.5	3000
Employment, Miller	791.17	121.27	624.5	874.5
Employment, All Importers	2425783.16	4230236.58	499.5	20000000
Employment, Coors Importers	3000.00	0	3000	3000
Employment, Miller Importers	11714285.43	7750576.28	5499999.5	20000000
# of Brands produced at each, All Breweries	9.68	5.65	1	20
# of Brands produced at each, Coors	8.86	6.4918	2	18
# of Brands produced at each, Miller	9.89	1.18	8	12
# of Brands produced at each, All Importers	1432.22	1395.84	112	3000
# of Brands produced at each, Coors Importers	3000.00	0.00	3000	3000
# of Brands produced at each, Miller Importers	8166666.17	970142.50	6499999.5	9500000

Table 2: Summary Statistics, Parent Company level

	Mean	Standard Deviation	Minimum	Maximum
All Breweries Number Breweries	1.26	1.43	1	13
All Breweries Total Brands	10.08	8.75	1	85
All Breweries Total Canlines	0.88	4.56	0	42
All Breweries Total Capacity	2232579.19	13042152.03	0	107999994
All Breweries Total Carbonated Bottling Lines	1.34	5.05	0	45
All Breweries Total Employment	376.18	1576.35	0	14269.5
Coors Number Breweries	2.33	0.58	2	3
Coors Total Brands	21.33	1.15	20	22
Coors Total Canlines	2.67	0.58	2	3
Coors Total Capacity	27333332.67	3175426.19	25499999.5	30999999
Coors Total Carbonated Bottling Lines	2.0000	0.0000	2	2
Coors Total Employment	3657.67	360.56	3449.5	4074
Miller Number Breweries	6.0000	0.0000	6	6
Miller Total Brands	21.67	2.31	19	23
Miller Total Canlines	16	0.0000	16	16
Miller Total Capacity	48999997.0000	0.0000	48999997	48999997
Miller Total Carbonated Bottling Lines	18.0000	0.0000	18	18
Miller Total Employment	4747.0000	0.0000	4747	4747



a) b)

Figure 8: These figures show the total employment at each Miller and Coors brewery, compared to the total employment at each other brewery in the BMC dataset. The Memphis, TN Plant shut down in 2006, so there is one less MillerCoors plant post merger.

Figure 9 shows the capacity for Miller and Coors before and after the merger, compared to its competitors. Similar to employment, Miller and Coors are on the higher end of the distribution for capacity, with the majority of their breweries above six million barrels. Most competitors fall far beneath that, with most capacities in the ten thousand to five hundred thousand range. A similar pattern holds for Figure 10, which shows that Miller and Coors were mostly in the upper distribution of canning and carbonated bottling lines among breweries.

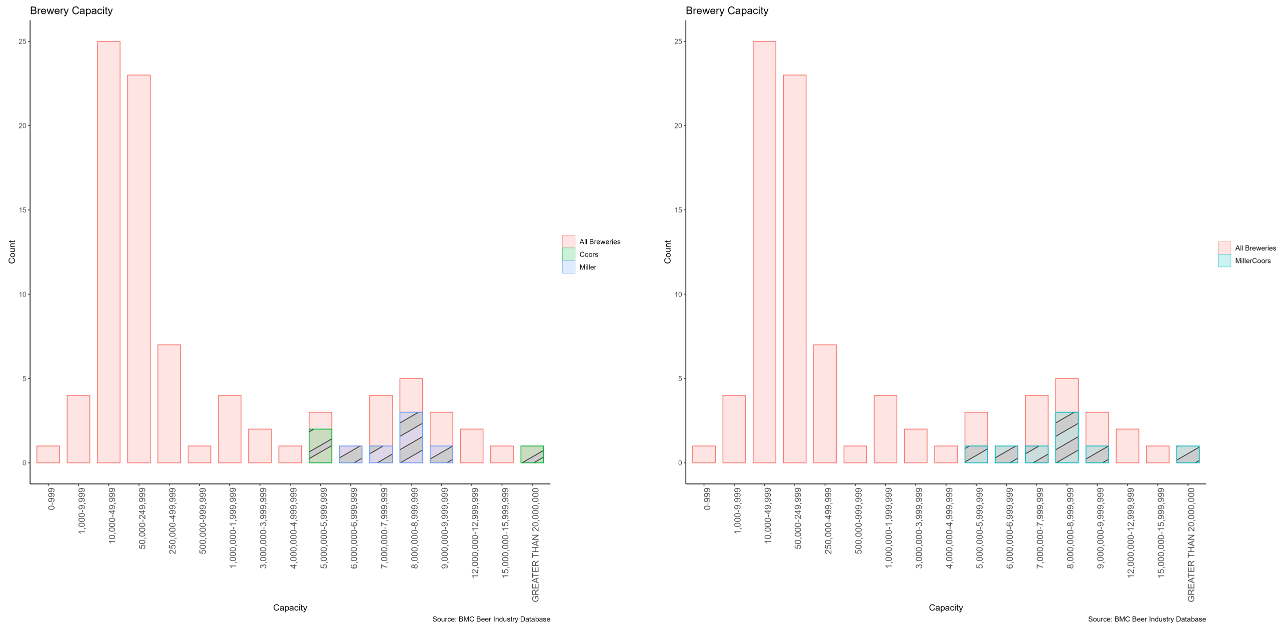


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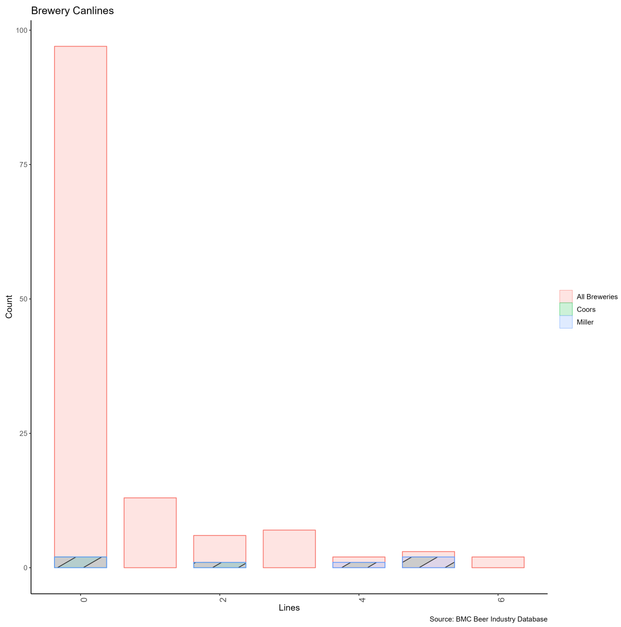
Figure 9: These figures show the total capacity at each Miller and Coors brewery, compared to the total capacity at each other brewery in the BMC dataset. Capacity is measured in barrels, typically, 31 Gallons or approximately 117 liters. The Memphis, TN Plant shut down in 2006, so there is one less MillerCoors plant post merger.



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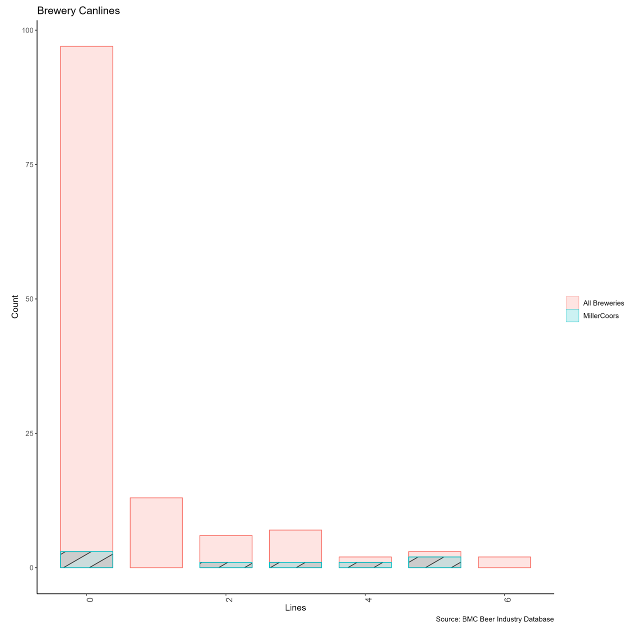

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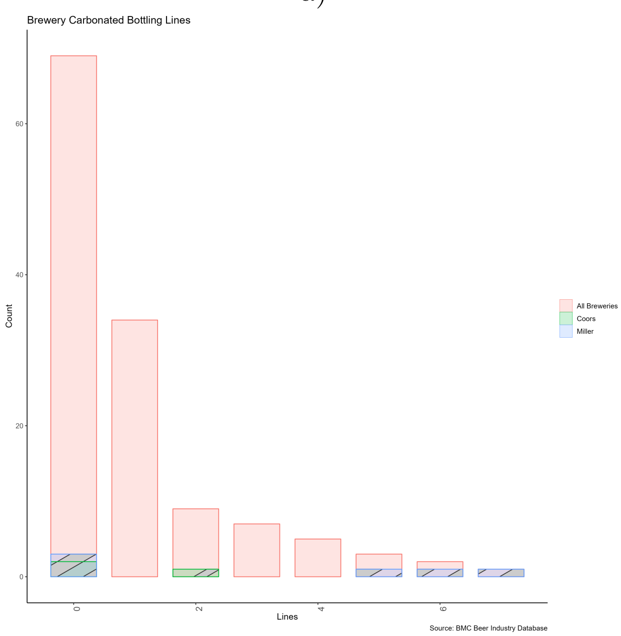

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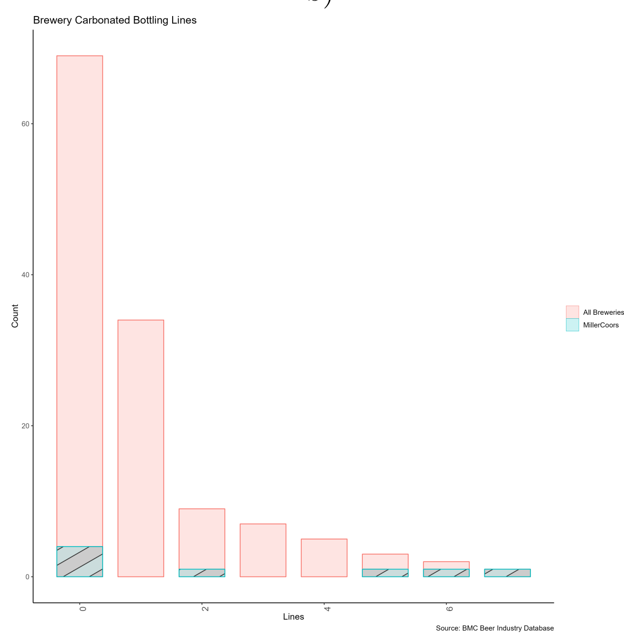
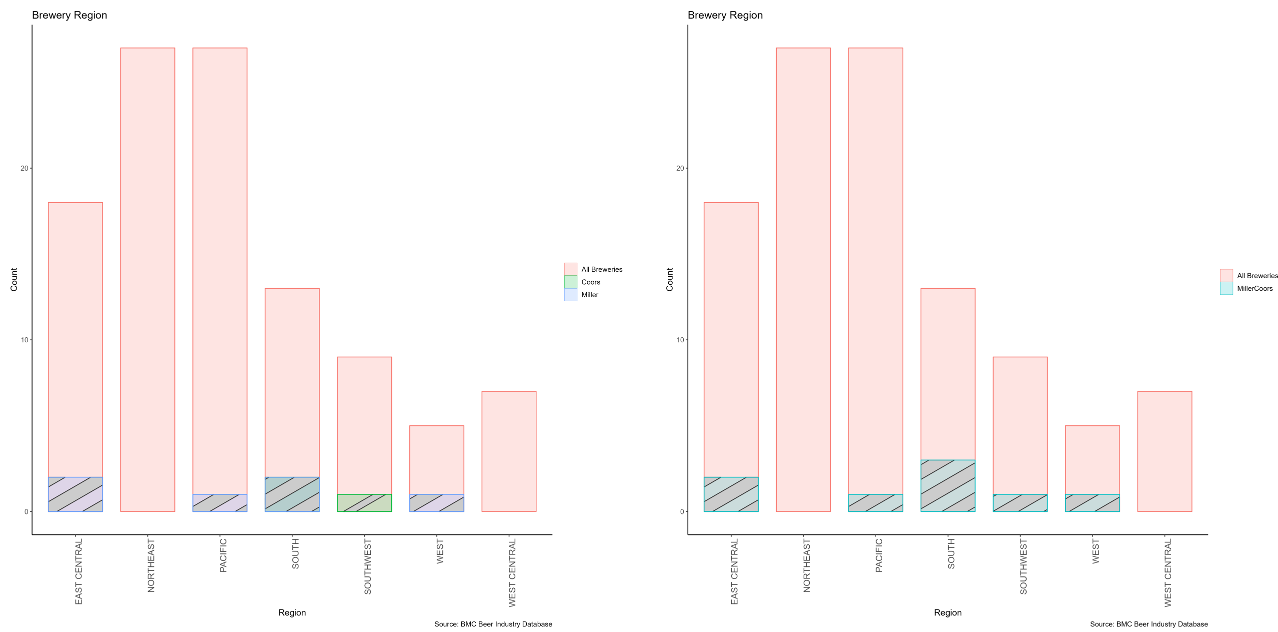


d)

Figure 10: These figures show the total canlines and carbonated canlines at each Miller and Coors brewery, compared to the total canlines and carbonated canlines at each other brewery in the BMC dataset. The Memphis, TN Plant shut down in 2006, so there is one less MillerCoors plant post merger.

Overall, these figures indicate Miller and Coors had a clear capital and employment advantage over most competitors. Regarding product variety, these companies had enough capacity and employees to sustain new varieties, and it also does not appear that the merger affected any of these aggregate variables that could have affected product variety.

Finally, Figure 11 compares the regional differences between Miller, Coors and their competitors. Two facts can be drawn from these figures. First, Coors and Miller had no overlap in region, which corroborates with comments made by regulators and spokespeople regarding reasons for the merger. Secondly, most breweries are located in the Northeast and the Pacific, and neither Miller or Coors have significant presence in the area. Only Miller has one brewery there.



a) b)

Figure 11: These figures show where each Miller and Coors brewery is located, compared to where each other brewery in the BMC dataset is located. The Memphis, TN Plant shut down in 2006, so there is one less MillerCoors plant post merger.

In sum, is likely that the merger happened due to these regional differences, and had little effect on aggregate capital and labor trends at the breweries and elsewhere. Therefore, any decisions on product variety were not due to changes at the aggregate level of capital and labor, but due to changes in distance, changes in distribution costs or market power.

1.5 Differences between the IRI dataset and the BMC Database

The IRI dataset and the BMC dataset differ in coverage due to the lack of categorization of parent companies in the BMC dataset. The BMC dataset's brewery database identifies breweries based on their name, while the IRI dataset identifies breweries based on their parent company and main vendor. As such, some brands that are subsidiaries of one company may not be listed as belonging to that company in the BMC database. Additionally, some subsidiary breweries are not in the BMC database, making it impossible to verify whether these brands were produced in the current time period. This mainly affects Miller, as the

Table 3

Year	Company	Missing Discontinued Brands	Missing New Brands	Percent of Discontinued Brands in IRI	Percent of New Brands in IRI
2007	Coors	2	5	-25%	42%
2008	Coors	3		-33%	
2009	Coors	2		-25%	
2010	Coors	4		-40%	
2007	Miller	6	7	-75%	58%
2008	Miller	6		-67%	
2009	Miller	4		-50%	
2010	Miller	5	1	-50%	50%
2008	MillerCoors	9	10	-100%	100%
2009	MillerCoors	8	1	-100%	100%
2010	MillerCoors	10	2	-100%	100%

This table shows the difference between brand coverage in the BMC database and the IRI database.

majority of their brands are from subsidiary companies. Table 3 shows the difference between the number of brands in the BMC database versus the IRI database per year and the percentage of brands that were considered new or discontinued in the IRI dataset that were not in the BMC database.

The lack of coverage in the BMC database ranges from 25% to 100%, making the BMC database for brands difficult to use for this paper. This is especially an issue for Miller, which have multiple subsidiaries not included in the BMC data, including Henry Weinhard, Mickey's, Hamm's, and Foster's. This change is further exacerbated by the merger, where the majority of products that leave the market are products from Miller subsidiaries. Due to this change, I use the IRI database for the majority of my analysis and use the brewery data to provide general information on production.

1.6 The Beverage Marketing Corporation Distributor Database

The Beverage Marketing Corporation Distributor data contains 9507 total distributors from 2006 to 2010. This dataset contains information on location, key personnel, parent companies they distribute from, employee count, sales count, and number of trucks. This data can be linked to the IRI dataset through the market level, as through conversations with the data providers and distributor employees, most distributors work within the market and do not travel across markets. Again, the data is given in ranges and topcoded, so the same data cleaning choices from the other Beverage Marketing Corporation datasets are used. Table 4 shows summary statistics for all distributors, distributors that distribute Coors products, and distributors that distribute Miller products.

Table 4: Summary Statistics, BMC Distributor Database

	Count			
Number of Unique Distributors	2080			
Number of Unique Distributors, Coors	826			
Number of Unique Distributors, Miller	769			
	Mean	Standard Deviation	Minimum	Maximum
All Distributors Employment	45.01	34.3216	1	100
All Distributors Sales	23781749.96	37129620.44	250000	200000000
All Distributors Trucks	17.88	19.41	1	100
Coors Distributors Employment	43.28	35.02	1	100
Coors Distributors Sales	22334800.86	36969137.02	250000	200000000
Coors Distributors Trucks	17.74	20.17	1	100
Miller Distributors Employment	42.38	35.02	1	100
Miller Distributors Sales	21626328.38	36119769.83	250000	200000000
Miller Distributors Trucks	17.33	19.98	1	100

This table shows summary statistics for distributors from 2006 to 2010.

2 Alternate Specification and Robustness Tests of the Difference-in-Differences Results

In this section, I describe an alternate specification where I estimate the model on the raw count of product variety, rather than log transformations. I also describe the two robustness checks for the difference-in-differences results: A synthetic control for the changes in Miller, Coors and MillerCoors varieties, and a placebo test to verify whether the merger's effect is due to the merger itself and not a spurious pretrend. I find the model is robust to these changes and robustness tests. An additional test, that of using de-trended data that removes potential annual trends prior to the merger, is included in the paper.

2.1 Difference-in-Differences Results without logs

The following section describes a different version of the difference-in-differences model and the results. Similar to the paper's model, this uses a subset of the firm's data alongside the Miller and Coors data to estimate how MillerCoors brand offerings compare in regards to competitors. Unlike the model in the paper, the dependent variable is the raw number of brands, rather than the log transformation. I use the model below to estimate the impact of the merger on the number of brands of each firm i, in each market m at each period t:

$$\text{num brands}_{imt} = \beta_1(\text{Post Merger}_t) + \beta_2(\text{Miller}_i + \text{Coors}_i) + \beta_3(\text{MillerCoors}_i) + \epsilon_{imt}$$

Where (Post Merger$_t$) is an indicator for whether the observation is after the completion of the merger, $\text{Miller}_i + \text{Coors}_i$ is a sum of the indicators for Miller and Coors brand, and MillerCoors_i is an indicator for whether the brand is a MillerCoors brand. The last coefficient acts as a difference-in-differences coefficient of interest, as it measures the additional impact of the number of brands after the merger and under the merged company, compared to the control group. As before, I employ two separate control groups and estimate the model for each.

Overall, the difference-in-differences coefficient is positive for the first group but null for the second group. Table 5 shows the difference-in-differences result when comparing against all products in the market. Here, the coefficient is 3.56 under all controls, implying that after the merger, MillerCoors gained 3.56 brands relative to all products. Comparisons between all breweries in the market and MillerCoors have potential issues relating to unobsevables, as described in the paper. Table 6 shows that for the second group, the difference-in-differences coefficient is indistinguishable from zero for every specifications of the model except the first. Given that the model in the paper ranges from a positive coefficient to a negative one under year fixed effects, this points towards a potential annual trend driving these results. I correct for this in the detrended models in the paper.

Table 5

	Dependent variable:				
	Number of Brands				
	(1)	(2)	(3)	(4)	(5)
Post Merger	5.006***	0.585***	0.545***	−0.142***	−0.164***
	(0.093)	(0.083)	(0.078)	(0.046)	(0.049)
Miller or Coors	38.835***	34.410***	34.395***	34.413***	34.414***
	(0.904)	(0.884)	(0.884)	(0.885)	(0.885)
MillerCoors	−0.880	3.544***	3.585***	3.564***	3.564***
	(0.613)	(0.613)	(0.607)	(0.604)	(0.604)
State FE	No	No	Yes	Yes	Yes
Month FE	No	Yes	Yes	No	Yes
Year FE	No	No	No	Yes	Yes
Observations	298,153	298,153	298,153	298,153	298,153
Adjusted R^2	0.400	0.494	0.495	0.495	0.495
Note:	*p<0.1; **p<0.05; ***p<0.01				

Note: The table above shows the difference-and-difference results under a non-logged dependant variable. All other estimation is conducted the same. Observations are at the firm–market–month–year level. The "Post Merger" variable indicates the period after July 2008, the start of the merged company's operation. All firms that product beer products in the IRI dataset are included in this regression. Standard errors clustered at the market level. For the last set of regressions, to remove colinearity with the year, month and Post Merger variable, the December fixed effect is removed.

Table 6

	Dependent variable:				
	Number of Brands				
	(1)	(2)	(3)	(4)	(5)
Post Merger	16.519***	3.911***	3.901***	0.211***	−0.074
	(0.306)	(0.217)	(0.214)	(0.081)	(0.091)
Miller or Coors	38.835***	26.217***	26.214***	26.244***	26.242***
	(0.904)	(0.870)	(0.862)	(0.861)	(0.861)
MillerCoors	−12.393***	0.225	0.235	0.210	0.213
	(0.476)	(0.587)	(0.585)	(0.585)	(0.585)
State FE	No	No	Yes	Yes	Yes
Month FE	No	Yes	Yes	No	Yes
Year FE	No	No	No	Yes	Yes
Observations	45,712	45,712	45,712	45,712	45,712
Adjusted R^2	0.524	0.667	0.672	0.674	0.674

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: The table above shows the difference-and-difference results under a non-logged dependant variable. All other estimation is conducted the same. Observations are at the firm–market–month–year level. The "Post Merger" variable indicates the period after July 2008, the start of the merged company's operation. Only the ten largest firms by national revenue share prior to 2007 are included in this regression. Standard errors clustered at the market level. For the last set of regressions, to remove colinearity with the year, month and Post Merger variable, the December fixed effect is removed.

2.2 Synthetic Control

The following section creates a synthetic control group for MillerCoors using the methods of Abadie and Gardeazabal (2003) to better compare product variety changes of the firm after the merger. This method uses a combination of control group units to create a better comparison to the treated group. In the context of this work, I create a convex combination of the breweries in the top five percentile to create a better control group for Miller, Coors and MillerCoors.

One issue with this method is that the control group differs greatly on levels. As shown in the figure in the paper, Anheuser-Busch Inbev is the most appropriate comparison group prior to the merger, so any synthetic control should use Anheuser-Busch Inbev. One solution could be to split MillerCoors into separate companies, so the synthetic control can better match both Miller and Coors on levels. This causes additional issues, as the following figures representing the synthetic control on just Miller, just Coors and MillerCoors show.

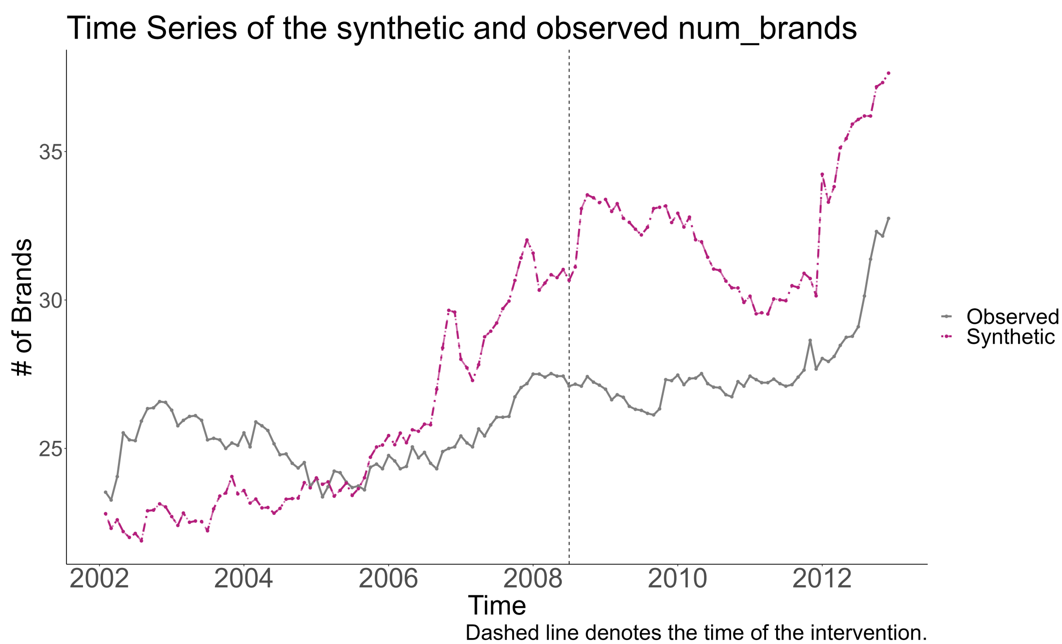
Figure 12 shows the synthetic control for Miller and Miller's observed outcomes. The post-period Miller observations are extrapolated by calculating the average share of Miller goods contributing to the simulated MillerCoors number of brands prior to the merger. Overall, the Miller synthetic control matches the pre-period fairly well, and the figure does suggest a positive relationship of product variety after the merger. However, Figure 13 and Figure 14 shows the synthetic control comparison for Coors and MillerCoors, respectively. Although these match better on levels than the control group, the large fluctuations prior to the merger are concerning for the parallel trends assumption.

In all three figures, the synthetic control is consistently above the number of brands observed by Miller, Coors and MillerCoors. With the synthetic control, I still observe the number of brands is less than what would be expected, so the merger still has a negative effect on the number of brands. As an additional statistic, I calculate the average difference after the merger between the observed and synthetic brands for all three scenarios. I find that the average difference for Miller and its synthetic counterpart, Coors and its synthetic counterpart and MillerCoors and its synthetic counterpart is 4.82 brands, 2.98 brands and 7 brands, respectively. This effect is lower than the difference-in-difference estimates of about 10 brands, but still shows a decline in the number of brands relative to their competitors.

2.3 Placebo Test

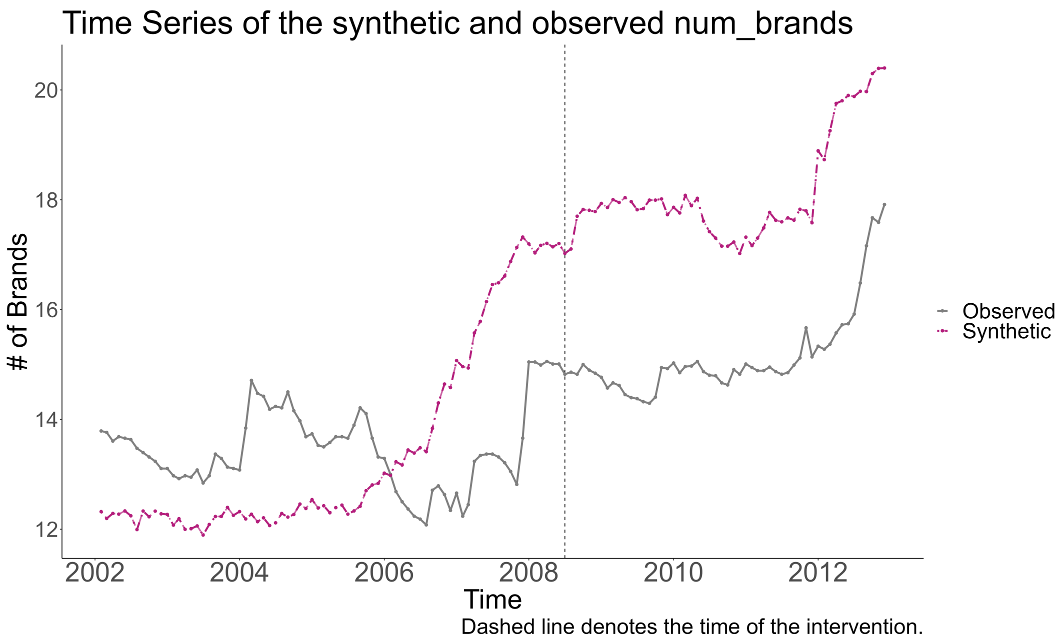
Here, I describe the Placebo Test, where I examine whether the same results are observed if the merger was moved July 2003 rather than July 2008. This is to address concerns that the results I am seeing are coming from the merger itself, rather than other trends. To do this, I remove the post July 2008 data, then re-estimate the model having adjusted the coefficients such that the merger occurs in July 2003 instead. This means the post merger dummy in the model is coded to at and after July 2003, and the MillerCoors dummy is also coded to at and after this date. If the coefficient is significantly different than the coefficient observed in the main results, then the main results are not caused by a spurious pre-trend and provides evidence that the main results are due to the merger itself.

Figure 12



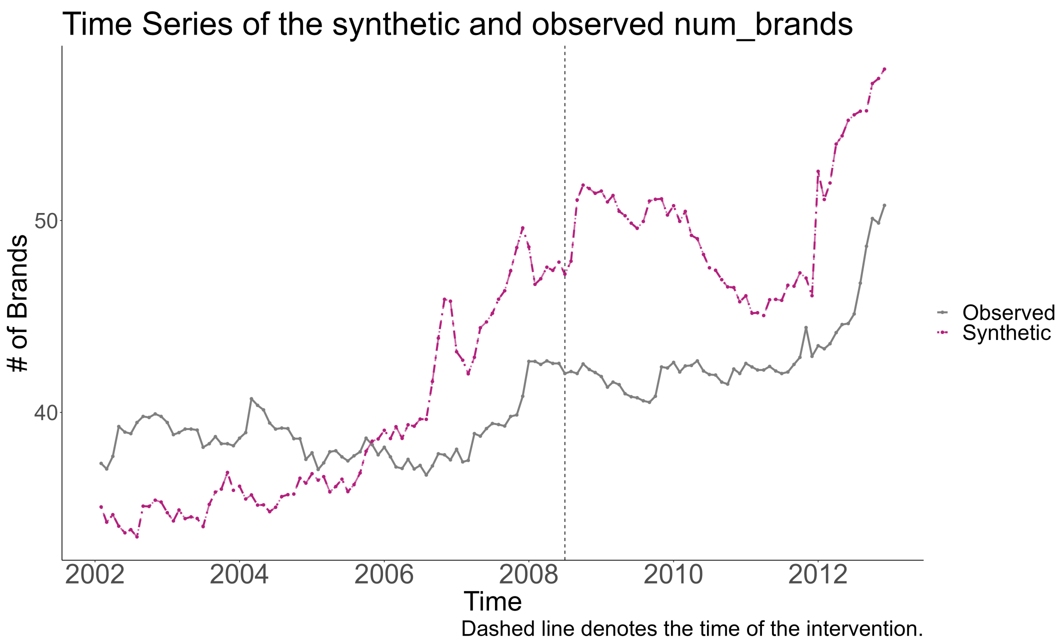
Note: This graph plots the average of the number of brands offered over all markets for Miller, and the synthetic control for Miller using firms within the top 5 percentile of market share. The Red dashed line denotes the date the MillerCoors merger was finalized. Miller is extrapolated to future periods by calculating the share that Miller goods contributed to MillerCoors prior to the merger, then taking the average. This value is approximately 0.63. Weights for the synthetic control are as follows: 39% for Anheuser-Busch, 60% for S&P Company, and negligible amounts for Boston Beer Company, Constellation Brands Inc, Yuengling & Son Inc, Deschutes Brewery, Diageo, and Heineken USA.

Figure 13



Note: This graph plots the average of the number of brands offered over all markets for Coors, and the synthetic control for Miller using firms within the top 5 percentile of market share. The Red dashed line denotes the date the MillerCoors merger was finalized. Coors is extrapolated to future periods by calculating the share that Miller goods contributed to MillerCoors prior to the merger, then taking the average. This value is approximately 0.36. Weights for the synthetic control are as follows: 70% for S&P Company, 20% for Diageo, 7.6 % for Anheuser-Busch, and negligble amounts for Boston Beer Company, Constellation Brands Inc, Yuengling & Son Inc, Deschutes Brewery, and Heineken USA.

Figure 14



Note: This graph plots the average of the number of brands offered over all markets for MillerCoors, and the synthetic control for MillerCoors using firms within the top 5 percentile of market share. The Red dashed line denotes the date the MillerCoors merger was finalized. MillerCoors is extrapolated to past periods by summing Miller and Coors before the merger. Weights for the synthetic control are as follows: 86% for AB-Inbev and 2% for S&P Company, Diageo, Boston Beer Company, Constellation Brands Inc, Yuengling & Son Inc, Deschutes Brewery, and Heineken USA.

I find the two difference-in-differences models for both brands and product variety pass the placebo test and estimate coefficients that are outside of the bounds of the baseline results. While some of these have the same sign as the baseline results, I interpret this as the merger had a stronger impact on an existing negative pre-trend. Table 7 shows the results for the placebo test for MillerCoors compared to all firms on brands, and Table 8 shows the results for the placebo test for MillerCoors compared to all firms at the brand level and at the product level. Table 9 and Table 10 shows the results for the placebo test for MillerCoors compared to all top firms at the brand level and at the product level.

Table 7

	Dependent variable:				
	log(Number of Brands)				
	(1)	(2)	(3)	(4)	(5)
Post Merger	1.005***	0.024*	0.023*	−0.008	−0.017**
	(0.016)	(0.014)	(0.014)	(0.009)	(0.008)
Miller or Coors	3.653***	2.670***	2.669***	2.669***	2.669***
	(0.022)	(0.023)	(0.023)	(0.023)	(0.023)
MillerCoors	−1.014***	−0.031**	−0.030**	−0.027**	−0.027**
	(0.018)	(0.012)	(0.012)	(0.012)	(0.012)
State FE	No	No	Yes	Yes	Yes
Month FE	No	Yes	Yes	No	Yes
Year FE	No	No	No	Yes	Yes
Observations	146,238	146,238	146,238	146,238	146,238
Adjusted R^2	0.516	0.614	0.615	0.616	0.616
Note:			*p<0.1; **p<0.05; ***p<0.01		

Note: The table above shows the results of the placebo test for the MillerCoors merger at the brand level. To conduct the placebo test, I remove all data at and after the merger's finalization date of July 2008, then set the Post Merger Dummy and the MillerCoors dummy to July 2003. These results show the comparison to all firms in the dataset as described by the paper. Observations are at the firm–market–month–year level. Standard errors clustered at the market level. For the last set of regressions, to remove colinearity with the year, month and Post Merger variable, the December fixed effect is removed.

3 Nested Logit Model Estimation

In this section I describe the estimation procedure in detail and which instruments are used. This project uses the pyBLP package in python developed by Conlon and Gortmaker (2020), which incorporates multiple best practices in estimation. I direct readers to Conlon and Gortmaker (2020) for further details on the package itself.

Table 8

	Dependent variable:				
	log(Number of Products)				
	(1)	(2)	(3)	(4)	(5)
Post Merger	1.305^{***}	0.014	0.013	0.005	−0.001
	(0.019)	(0.017)	(0.016)	(0.010)	(0.010)
Miller or Coors	4.836^{***}	3.545^{***}	3.545^{***}	3.545^{***}	3.545^{***}
	(0.029)	(0.032)	(0.033)	(0.033)	(0.033)
MillerCoors	-1.326^{***}	-0.035^{*}	-0.034^{*}	-0.033^{*}	-0.033^{*}
	(0.024)	(0.018)	(0.018)	(0.018)	(0.017)
State FE	No	No	Yes	Yes	Yes
Month FE	No	Yes	Yes	No	Yes
Year FE	No	No	No	Yes	Yes
Observations	146,238	146,238	146,238	146,238	146,238
Adjusted R^2	0.540	0.644	0.646	0.646	0.646
Note:			*p<0.1; **p<0.05; ***p<0.01		

Note: The table above shows the results of the placebo test for the MillerCoors merger at the product level. To conduct the placebo test, I remove all data at and after the merger's finalization date of July 2008, then set the Post Merger Dummy and the MillerCoors dummy to July 2003. These results show the comparison to all firms in the dataset as described by the paper. Observations are at the firm–market–month–year level. Standard errors clustered at the market level. For the last set of regressions, to remove colinearity with the year, month and Post Merger variable, the December fixed effect is removed.

Table 9

	Dependent variable:				
	Number of Brands				
	(1)	(2)	(3)	(4)	(5)
Post Merger	2.186***	0.086***	0.087***	−0.0003	−0.020**
	(0.024)	(0.017)	(0.017)	(0.007)	(0.008)
Miller or Coors	3.653***	1.549***	1.548***	1.548***	1.547***
	(0.022)	(0.031)	(0.031)	(0.031)	(0.030)
MillerCoors	−2.194***	−0.090***	−0.090***	−0.086***	−0.086***
	(0.021)	(0.014)	(0.014)	(0.014)	(0.014)
State FE	No	No	Yes	Yes	Yes
Month FE	No	Yes	Yes	No	Yes
Year FE	No	No	No	Yes	Yes
Observations	25,577	25,577	25,577	25,577	25,577
Adjusted R^2	0.765	0.905	0.906	0.907	0.907
Note:	*p<0.1; **p<0.05; ***p<0.01				

Note: The table above shows the results of the placebo test for the MillerCoors merger at the brand level. To conduct the placebo test, I remove all data at and after the merger's finalization date of July 2008, then set the Post Merger Dummy and the MillerCoors dummy to July 2003. These results show the comparison to the ten largest firms by national revenue share prior to 2007 as described by the paper. Observations are at the firm–market–month–year level. Standard errors clustered at the market level. For the last set of regressions, to remove colinearity with the year, month and Post Merger variable, the December fixed effect is removed.

Table 10

	Dependent variable:				
	Number of Brands				
	(1)	(2)	(3)	(4)	(5)
Post Merger	2.928^{***}	0.136^{***}	0.137^{***}	0.020^{**}	-0.007
	(0.029)	(0.021)	(0.021)	(0.009)	(0.011)
Miller or Coors	4.836^{***}	2.040^{***}	2.042^{***}	2.042^{***}	2.041^{***}
	(0.029)	(0.034)	(0.034)	(0.034)	(0.034)
MillerCoors	-2.949^{***}	-0.153^{***}	-0.154^{***}	-0.151^{***}	-0.150^{***}
	(0.027)	(0.020)	(0.020)	(0.020)	(0.020)
State FE	No	No	Yes	Yes	Yes
Month FE	No	Yes	Yes	No	Yes
Year FE	No	No	No	Yes	Yes
Observations	25,577	25,577	25,577	25,577	25,577
Adjusted R^2	0.776	0.916	0.918	0.918	0.918

Note: *p<0.1; **p<0.05; ***p<0.01

Note: The table above shows the results of the placebo test for the MillerCoors merger. To conduct the placebo test, I remove all data at and after the merger's finalization date of July 2008, then set the Post Merger Dummy and the MillerCoors dummy to July 2003. These results show the comparison to the ten largest firms by national revenue share prior to 2007 as described by the paper. Observations are at the firm–market–month–year level. Standard errors clustered at the market level. For the last set of regressions, to remove colinearity with the year, month and Post Merger variable, the December fixed effect is removed.

3.1 Estimation Strategy

Central to the estimation strategy is the nested fixed point procedure of Berry, Levinsohn, and Pakes (1995). I estimate the model given the population moment condition $E[Z'\omega(\theta_0^D)] = 0$, where $\omega(\cdot)$ is defined as per the optimization solution, $\theta_0^D = (\alpha, \Sigma, \rho)$ are the population parameters, where Σ is a diagonal matrix consisting of the σ parameters on the random coefficient shocks, and α consists of all α parameters on the model, and Z is a matrix of instruments. This model is solved through a generalized method of moments (GMM) estimator where I solve for the following for some positive definite weighting matrix A:

$$\theta^D = \arg\min_{\theta} \omega(\theta)' Z A^{-1} Z' \omega(\theta)$$

For any set of candidate parameters, this contraction mapping identifies the mean utility that matches observed and predicted market shares.

I use the two-step Hansen procedure for GMM estimation. In the fist step, $A = Z'Z$. Once the error is minimized, I re-estimate the model using an optimal weighting matrix that uses cluster correction to correct for autocorrelation, heteroscedasticity, and within-state correlations. As the number of regions increases, asymptomatic consistency is reached.

3.2 Instruments

In order to estimate the model, an instrument for price, an instrument for the nests, and an instrument for each nonlinear parameter is needed. Since prices are likely to be correlated with the structural error term given firms price optimally given product- and market-specific consumer values, I have a standard endogeneity issue. Additionally, due to the presence of the nests and the nonlinear parameters, I have a simultaneity issue where demand parameters cannot be jointly separated from market shares. Therefore, I need to address the endogeneity from these demand parameters and the nesting parameter, which helps us separately estimate the two.

To best compare the model from Miller and Weinberg's 2017 model, I use the instruments from their replication files. This is to best compare their model's findings to this model and keep as much similarity between the two models as possible. This provides the following instruments: A group indicator for whether the product is either Miller or Coors at or after 2008, distance from the nearest brewery times the price of gas for both these breweries and the other breweries in the dataset, the number of products in the market for both groups, the distance from breweries to each market, summed, these two variables interacted with dummies for whether the product is MillerCoors or Anheuser-Busch InBev, and the mean income of each market interacted with the imported, lite and ale dummies. Justification for these instruments can be found in their paper.

One key caveat of using their instrument requires an assumption for the instrument that identifies the nested logit parameter, which is the correlation between unobserved preferences for goods within the nest. For this, an instrument is needed such that it is uncorrelated with the structural error term, and provides exogenous variation in the conditional share of the goods within the nest. For this, I use the number of products in each nest as in Miller and Weinberg (2017). Although the main counterfactuals rely on product variety, I justify this through a timing assumption. I assume that firms choose product varieties per year, then, conditional on observables (characteristics of the good) and unobservables (random shocks), consumers then choose which product type they want and what specific product.This argument is akin to the selection on observables and unobservables argument made in Dale and Krueger (2002). The number of products in each nest is a standard instrument that is negatively correlated with the conditional share. Finally, I need instruments for parameters on consumer heterogeneity for preferences on characteristics. For this, I use mean income interacted with each product characteristic. These characteristics are different than Miller and Weinberg (2017). I assume that the structural error term is mean independent of income and product characteristics, a standard assumption in the literature. This provides me with a total of 12 instruments.

4 Alternative Counterfactuals

In this section, I describe the two alternate counterfactuals conducted to estimate what potential effect the merger could have on product variety. Two estimate the value of new products when discontinued products also exist in the market, and the value of discontinued products if no new products existed in the market. These counterfactuals require the second model which includes discontinued products and new products together, so all assumptions made about discontinued products existence in the market are kept. More details can be found within the main paper on these assumptions.

4.1 Value of New Products if Discontinued Products Remained in the Market

In this counterfactual, I estimate the value of new products under the scenario where discontinued products remain in the market the entire time. This counterfactual considers a scenario where if the merger were to not occur, both new products would not be created and discontinued products would not be eliminated. This model puts stronger assumptions on how a firm may act after the merger by stating the merged firm would keep all products in the market and not remove discontinued products as observed in the current equilibrium.

To estimate this, I first estimate consumer welfare in a version of the model where the underlying data includes new and discontinued products. I remove new products from the data, and re-estimate consumer welfare. Taking the difference and dividing it by consumer welfare under the case where both new and discontinued products were in the market, I am able to provide an estimate for the value of new products under this alternate scenario. I again consider two cases: one where prices remain static, and another where prices re-

Table 11: Change in Consumer Surplus Estimating Value of New Products if Discontinued Products Remain

		Time	Δ CS, Prices Fixed	Δ CS, Prices Adjust
Brands added to any market				
	Nested Logit	Monthly	1.0491 %	0.9585 %
		Quarterly	0.7099 %	0.6409 %
	RCNL	Monthly	1.0491 %	0.9584 %
		Quarterly	0.7087 %	0.6401 %

adjust after observing the change in product variety. Table 11 shows the results for this counterfactual.

Overall, I find the value of new products is slightly lower than the baseline results in the paper, but still positive. The estimates range from 0.64% to 1.04%, which for comparison, the results for the baseline model range from 1.12% to 1.35%. One potential explanation for this could be due to substitution between new and discontinued products. If new and discontinued products were substitutes of each other, then keeping both in the market would dampen the effect of new products since discontinued products already exist and serve similar customers. Examining this issue further would require both products to exist within the market concurrently, which does not hold for a long enough period of time within my dataset.

4.2 Value of Discontinued Products if New Products Never Existed

In this counterfactual, I estimate the value of discontinued products under the scenario where new products were never created. This counterfactual considers a scenario where if the merger were to not occur, both discontinued products would not be removed and new products would not be created at all. This model puts stronger assumptions on how a firm may act after the merger by stating the merged firm would still discontinue products and not create new products if a merger were to occur.

To estimate this, I first estimate consumer welfare in a version of the model where the underlying data includes no new products but discontinued products. I then remove discontinued products from the data, and re-estimate consumer welfare. Taking the difference and dividing it by consumer welfare under the case where there were no new products but discontinued products were in the market, I am able to provide a change in consumer welfare value for discontinued products. I again consider two cases: one where prices remain static, and another where prices re-adjust after observing the change in product variety. Table 12 shows the results for this counterfactual.

Overall, I find the value of discontinued products is lower than the baseline results in the paper, but still results in a consumer welfare loss. The estimates range from -0.03% to approximately -0.04%, which for comparison, the results for the baseline model range from

Table 12: Change in Consumer Surplus Estimating Value of Discontinued Products if New Products Never Existed

		Time	Δ CS, Prices Fixed	Δ CS, Prices Adjust
Brands readded to all markets in which originally discontinued, then withdrawn				
	Nested Logit	Monthly	-0.0351%	-0.0369%
		Quarterly	-0.0331%	-0.0353%
	RCNL	Monthly	-0.0351%	-0.0369%
		Quarterly	-0.0331%	-0.0353%

Table 13: Attributes of New Products in Dataset and in Structural Subsample

		Mean	Standard Deviation	Minimum	Maximum
New Products					
	Revenue of Products	333023.68	556088.33	2251678.35	10.28
	Total Products Bought	45987.03	65211.1	259939	1
	Market Share	0.0006	0.001	0.0041	1.86×10^{-8}
	Number of Stores Sold at	31.15	29.97	85	1
New Products Used in Structural Model					
	Revenue of Products	679183.81	702753.81	2251678.35	3538.64
	Total Products Bought	77791.42	77131.62	259939	512
	Market Share	0.0012	0.0012	0.0041	6.11×10^{-6}
	Number of Stores Sold at	47.92	33.49	85	6
		Sum			
	Total Revenue of All New Products	19981421.16			
	Total Revenue of All New Products Used in Structural Model	17658779.08			

Note: The table above shows summary statistics between new products used in the structural model versus new products in the dataset.

-0.14% to -0.17%. One potential explanation for this could be consumers may substitute towards other goods in the market or go to the outside good more often than if there were no new products. Discontinued products could matter less when no new products from the merged firm exist to potentially take their place.

5 Attributes of New and Discontinued Products Used in the Structural Models

In this section, I describe key attributes of new and discontinued products used in the structural models. Due to the data limitations for model estimation as described in the paper, I can only consider products that are sold in each month or in each quarter per year and products that are sold at least twenty or more times. This limits the number of products considered in the structural estimation. Table 13 describes the attributes of new products, compared to the attributes of all new products in the dataset. Table 14 describes the attributes of discontinued products, compared to the attributes of all discontinued products in the dataset.

Table 14: Attributes of Discontinued Products in Dataset and in Structural Subsample

		Mean	Standard Deviation	Minimum	Maximum
Discontinued Products					
	Revenue of Products	20295.29	61408.98	284994.95	12.58
	Total Products Bought	8006.19	29331.36	135013	1
	Market Share	3.6434×10^{-5}	0.0001	0.0005	2.1707×10^{-8}
	Number of Stores Sold at	10.38	14.38	57	1
Discontinued Products Used in Structural Model					
	Revenue of Products	15787.18	14568.91	36342.02	3538.64
	Total Products Bought	1925.5	1265.35	3356	512
	Market Share	2.7242×10^{-5}	2.5140×10^{-5}	6.2710×10^{-5}	6.1062×10^{-6}
	Number of Stores Sold at	16.25	17.17	42	7
		Sum			
	Revenue of Products	426201.18			
	Total Revenue of All Discontinued Products Used in Structural Model	63148.76			

Note: The table above shows summary statistics between discontinued products used in the structural model versus discontinued products in the dataset.

Overall, the differences between attributes of new and discontinued products in the structural model subsample directly come from the data restrictions. Overall, new and discontinued products in the model have higher average revenues, bought products, market share and number of stores sold at. Likewise, the standard deviations are lower for all variables due to a smaller sample. Maximums match between the population and the subsample for most variables, and minimums are higher in the subsample. These all are sensible changes due to the restriction made on the data, where these discontinued and new products must be sold more often.

However, the total revenue of new and discontinued products in the population and in the subsample indicate that while most of the new products are captured in the model, not as many discontinued products are. The total revenue of new products in the subsample is \$17,658,779.08, which compared to the population, is \$19,981,421.16, meaning 88% of new product revenue is represented in the model. The total revenue of discontinued products in the subsample is \$63,148.76, which compared to the population, is \$426,201.18, meaning 15% of discontinued product revenue is represented in the model. This is due to the restriction itself. Since a product must be sold at least twenty times, most discontinued products are sold very infrequently in this dataset before ultimately being discontinued. Therefore, while new products are sold and bought almost immediately, discontinued products are eventually phased out, leading to a potential downward bias on the value of discontinued products.

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