# Bowing to Five Pecks of Rice: How Online Monetization Programs Shape Artistic Novelty

Online Appendix

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**Note**: This document is the appendix for the article, *Bowing to Five Pecks of Rice: How Online Monetization Programs Shape Artistic Novelty*, forthcoming in *Chinese Sociological Review*.

# 1 Supplementary information

## 1.1 Procedure of identifying organizational structures

Because all the songs released by the transnational music conglomerates ("Big Three") are excluded from the data, I consider those that share similar traits to the "Big Three" as major companies. Specifically, I regard a company as a major company if it has high capital assets, diverse stakeholders, and active acquisition of small competitors (Hesmondhalgh, 2007; Peterson & Anand, 2004).

To identify these companies, I collected extensive information from the credit investigation institutions. The credit investigation institutions are those who collect, arrange, save, and process the credit information of enterprises, public institutions, other organizations, as well as individuals. Private credit investigation firms usually can provide users with information on a requested company, including its structure, assets, investors, and business details such as the history of acquisitions or the change of owners. Some of the information is open to public inquiry, though not without conditions. I collected most of my organizational data on qcc.com, one of the most popular credit investigation firms in China, and all the four criteria mentioned above for each company were accessible at the time of my data collection in 2020. In cases where the organization cannot be found on qcc.com, which indicates that the name is not a formal business entity, I validate it by using the National Enterprise Credit Information Publicity System, the official database that stores registered business entities.

In the database of these credit investigation institutions, I searched the organizational structure and the investors of each of the 466 names. Based on the information, I identified 17 major companies that meet all of the following criteria similar to the "Big Three": listing entertainment or cultural activities as one of the main businesses; investing and controlling at least one satellite company; having more than one stakeholder; claiming a registered capital above 10 million RMB (ca. 1.4 million dollars), <sup>1</sup> the minimum requirement for registering a company limited by shares in China, by the time of its first song release in the dataset. The reason to set up a criterion as such is that the company is structured hierarchically with high a financial stake and multiple decision-makers so that the musicians are supposed to have restrained artistic discretion. In addition to these companies, I also found 14 companies that are directly controlled by a government entity or a public institution, which I also classified as major for the fact that these companies are endorsed publicly and structured as part of the bureaucratic functionality of serving the public interest. The musicians associated with these companies

<sup>&</sup>lt;sup>1</sup>The minimum registered capital requirement for establishing a company was nullified by the 2013 amendment of the Company Law, which was within the time span of my analysis. However, the abolishment of the requirement was primarily for sweeping the obstacle for starting up new companies, and the existing companies did not tend to reduce their registered capital after the requirement abolishment. The fact that major companies still claim a high registered capital after the requirement abolishment demonstrates their heavy investment and high stake in the business.

nies are necessarily constrained by the political and economic interests of the government (Baranovitch, 2003). Therefore, I identified 31 major companies in total from my dataset, which reflects the fragmented market of the Chinese popular music industry (Qu, Hesmondhalgh, & Xiao, 2021).

For the rest of the company names in the dataset, I identified 234 of them that could not be found by the credit investigation institutions, which I view as self-releasing musicians. Many of these "company names" are the name of the musicians themselves, indicating that the musicians pursued their artistic creation without formal organizational support or constraint. The fact that they did not establish a profit-seeking legal entity also suggests that economic return is not the primary goal of their musical activity, which is the case for amateur musicians who are under this category.

The last 197 companies that can be found on the credit investigation institutions but are not major companies then become indie companies. They are generally lightly invested and structured in a less hierarchical way, in which only one or two investors, who sometimes are the musicians themselves, control the company. They may also be the satellite subsidiary of or acquired by the major company as a part of the vertical integration strategy of the latter (Caves, 2003). By virtue of being a smaller, subsidiary of the major, however, the musicians in these indie companies are usually supposed to have higher artistic autonomy under the financial safety net provided by the major company (Dowd, 2004; Lopes, 1992).

## References

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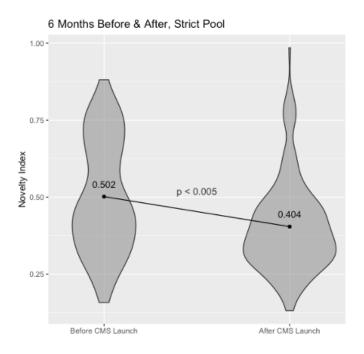
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#### 1.2 Robustness check

To verify that the shift in the novelty level of the songs is driven by the launch of the monetization program rather than the outcome of random fluctuation, I use the following ways to check the robustness of the results. I used a more selective group of musicians as the sample of analysis. In the original dataset, not all musicians released songs both before and after the CMS launch within the range of our dataset. Moreover, there are a few musicians who changed producer identity (genre) or organizational structure (company type) after the CMS launch. I contend that this will not hurt my major findings in the main article as my claim is at the aggregate level instead of the musician level so that the change of producer type of individual musicians will not significantly confound the finding. However, to test the robustness of the results, I subset the songs written by the musicians who have released songs both before and after the CMS launch in my dataset and who have not changed their producer type. I ended up with a smaller dataset with 1,223 songs written by 52 musicians. The result still holds in general for this selective group of musicians. Above all, the pooled novelty level of the songs even more significantly dropped after the CMS launch in this group, as shown in the graphic below.



## 2 Tables

# 2.1 Constructing Novelty Index

The table shows the 26 sonic features that I used for constructing the measurement of musical novelty. These features are widely used in the music industry for musical tasks such as pattern recognition and instrument separation. The name of each feature, as well as their name in the librosa package, which I used to extract them, are given. Additionally, I also add a brief description of what each feature describes and captures in terms of the sonic quality of music. Finally, I present the mean and standard deviation of the raw scores that I extracted from librosa, as well as the normalized mean and standard deviation that I actually used for comparing the song similarity.

Table 1: The acoustic features used for constructing Novelty Index.

Feature Name (in	Description	Raw Mean	Normalized
librosa)		(SD)	Mean (SD)
Chroma Features	Chroma features are a powerful tool for detect-	0.334 (0.073)	0.420 (0.091)
(chroma_stft)	ing pitches. One major use of chroma features is		
	to capture harmonic and melodic characteristics		
	of music.		
Root-Mean-Square	This measurement calculates the root-mean-	0.175 (0.079)	0.223 (0.101)
of Spectrogram	square of each frame in the Spectrogram of the		
Frames (rms)	song, which consists of short time frames in		
	which the signal strength at various frequencies		
	is identified.		
Spectral Centroid	Spectral centroid measures the center of the	2048.881	0.287 (0.079)
(spectral_centroid)	mass of a song's spectrum, or the frequency	(564.7667)	
	components of the sound. The measurement		
	can be used to capture whether the song tends		
	to be of high-frequencies or low-frequencies.		
Spectral Band-	Spectral bandwidth delineates the variance of	2282.332	0.655 (0.120)
width (spec-	the song's sound with respect to the spectral cen-	(419.345)	
tral_bandwidth)	troid, which is often used to describe the per-		
	ceived timbre of the sound.		

Spectral Roll-Off	Spectral roll-off is the frequency below which a	4330.900	0.485 (0.143)
(spectral_rolloff)	specified percentage of the total spectral energy	(1277.314)	
	(85% in this case following the industry stan-		
	dard) lies.		
Zero-Crossing Rate	Zero-Crossing Rate is the rate at which the	0.085 (0.033)	0.120 (0.046)
(zero_crossing_rate)	sound signal changes from positive to negative		
	or from negative to positive, usually used to de-		
	tect the appearance of sound.		
Mel-Frequency	The Mel-frequency cepstral coefficients of a sig-	-134.856	0.774 (0.070)
Cepstral Coeffi-	nal are a small set of features (usually about 10-	(90.210)	
cients (MFCC) #1	20) that concisely describe the overall shape of		
(mfcc)	a spectral envelope. In MIR, it is often used		
	to describe timbre. In this case, I extracted 20		
	MFCCs, the rest of which are presented below.		
MFCC #2		100.640	0.457 (0.095)
		(26.317)	
MFCC #3		7.479 (18.177)	0.649 (0.083)
MFCC #4		27.584	0.547 (0.085)
		(12.067)	
MFCC #5		4.535 (8.989)	0.589 (0.099)
MFCC #6		6.614 (8.807)	0.604 (0.090)
MFCC #7		-0.541 (7.231)	0.623 (0.079)
MFCC #8		2.964 (7.842)	0.572 (0.115)
MFCC #9		-5.897 (7.110)	0.594 (0.095)
MFCC #10		2.511 (6.482)	0.584 (0.104)
MFCC #11		-6.368 (6.370)	0.545 (0.089)
MFCC #12		-0.278 (6.144)	0.514 (0.103)
MFCC #13		-5.332 (5.327)	0.583 (0.085)
MFCC #14		-0.926 (5.081)	0.523 (0.099)
MFCC #15		-4.914 (4.646)	0.514 (0.107)
MFCC #16		-0.708 (4.836)	0.671 (0.095)
MFCC #17		-6.140 (4.396)	0.538 (0.089)

MFCC #18	-0.095 (4.378)	0.573 (0.100)
MFCC #19	-4.678 (3.986)	0.454 (0.090)
MFCC #20	-0.869 (4.289)	0.515 (0.103)

# 2.2 Regression tables

The following results are based on linear regression models of the independent variables and the covariates on the dependent variables. To mitigate the concern about heteroskedasticity in the data, I also tested all the models using heteroskedasticity-consistent standard errors, known as "HC3", and check the value and significance of the coefficients. The results hold for all the regressions and are hence not reported here.

Table 2: Pooled OLS Regression of Musical Novelty on CMS Launch, Different Time Windows

		5-Month Window			12-Month Window			Full Data	
	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)
Program Launch	-0.033*** (0.009)	-0.021 (0.013)	-0.018 (0.013)	-0.034*** (0.007)	-0.038*** (0.009)	-0.029** (0.009)	—0.005 (0.003)	-0.006 (0.005)	-0.004 (0.005)
Market Dominance		-0.037** (0.014)	-0.038** (0.014)		-0.047*** (0.009)	-0.042*** (0.010)		-0.020*** (0.004)	-0.015*** (0.004)
Identity: Pop (Baseline: Hip-Hop)		0.041**	0.048**		0.026*	0.025*		0.046***	0.048***
Identity: Rock		0.087***	0.078***		0.020 (0.011)	0.016 (0.011)		0.037***	0.034***
Identity: Folk		0.076***	0.078***		0.075***	0.069***		0.096***	0.093*** (0.004)
Indie (Baseline: Major)		-0.003 (0.018)	0.009		0.008 (0.012)	0.011 (0.012)		-0.013* (0.006)	-0.011 (0.006)
Self-Releasing		0.053**	0.065***		0.008	0.010 (0.011)		-0.002 (0.006)	-0.001 (0.006)
Newcomer		-0.008 (0.013)	-0.013 (0.013)		0.012 (0.009)	0.007		0.002 (0.004)	0.001 (0.004)
Performer/Composer			0.023*			0.033***			0.033***
Group Musician			0.036***			-0.004 (0.007)			-0.002 (0.003)
Constant	0.435***	0.348***	0.308***	0.438***	0.403***	0.373***	0.415***	0.374***	0.346***
Observations R <sup>2</sup> Adjusted R <sup>2</sup> Residual Std. Error	922 0.014 0.013 0.135 (df = 920)	922 0.096 0.088 0.130 (df = 913)	922 0.113 0.104 0.129 (df = 911)	2,213 0.012 0.012 0.012 0.142 (df = 2211)	2,213 0.048 0.044 0.140 (df = 2204)	2,213 0.055 0.050 0.140 (df = 2202)	11,297 0.0002 0.0001 0.136 (df = 11295)	11,297 0.046 0.045 0.133 (df = 11288)	11,297 0.054 0.053 0.132 (df = 11286)

Table 3: Pooled OLS Regression of Musical Novelty on CMS Launch, Divided by Market Position

	L	Dependent variable: Novelty Inc	dex
	(1)	(2)	(3)
Program Launch	-0.032***	-0.037***	-0.029**
	(0.007)	(0.010)	(0.010)
Market Dominance	-0.034*	-0.043**	-0.041*
	(0.016)	(0.016)	(0.016)
Program Launch ×	-0.010	-0.007	-0.001
Market Dominance	(0.019)	(0.019)	(0.019)
Identity: Pop		0.026*	0.025*
(Baseline: Hip-Hop)		(0.010)	(0.010)
Identity: Rock		0.021	0.016
		(0.011)	(0.011)
Identity: Folk		0.075***	0.069***
		(0.011)	(0.011)
Indie		0.007	0.011
(Baseline: Major)		(0.012)	(0.012)
Self-Releasing		0.007	0.010
		(0.011)	(0.011)
Newcomer		0.012	0.007
		(0.009)	(0.009)
Performer/Composer			0.033***
			(0.008)
Group Musician			-0.004
			(0.007)
Constant	0.442***	0.402***	0.373***
	(0.006)	(0.015)	(0.017)
Observations	2,213	2,213	2,213
$R^2$	0.022	0.048	0.055
Adjusted R <sup>2</sup>	0.020	0.044	0.050
Residual Std. Error	0.142 (df = 2209)	0.140 (df = 2203)	0.140 (df = 2201)
F Statistic	16.369*** (df = 3; 2209)	12.221*** (df = 9; 2203)	11.567*** (df = 11; 2201

\*p<0.05; \*\*p<0.01; \*\*\*p<0.001

Table 4: Pooled OLS Regression of Musical Novelty on CMS Launch, Divided by Producer Identity

	I	Dependent variable: Novelty Ind	lex
	(1)	(2)	(3)
Program Launch	0.002	-0.014	0.0005
	(0.022)	(0.023)	(0.023)
dentity: Pop	0.059**	0.053*	0.056**
Baseline: Hip-Hop)	(0.021)	(0.021)	(0.021)
Program Launch ×	-0.048*	-0.038	-0.041
Pop	(0.024)	(0.024)	(0.024)
dentity: Rock	0.054*	0.044	0.047*
	(0.023)	(0.023)	(0.023)
Program Launch ×	-0.041	-0.030	-0.040
Rock	(0.026)	(0.026)	(0.026)
dentity: Folk	0.074**	0.073**	0.077***
	(0.022)	(0.022)	(0.022)
Program Launch ×	0.0005	0.009	-0.004
Folk	(0.026)	(0.026)	(0.026)
Market Dominance		-0.045***	-0.040***
		(0.009)	(0.010)
ndie		0.012	0.015
Baseline: Major)		(0.012)	(0.012)
Self-Releasing		0.011	0.013
		(0.011)	(0.011)
Newcomer		0.011	0.007
		(0.009)	(0.009)
Performer/Composer			0.032***
			(0.008)
Group Musician			-0.004
			(0.007)
Constant	0.381***	0.381***	0.348***
	(0.020)	(0.023)	(0.024)
Observations	2,213	2,213	2,213
$\mathbb{R}^2$	0.037	0.051	0.058
Adjusted R <sup>2</sup>	0.034	0.047	0.052
Residual Std. Error	0.141 (df = 2205)	0.140 (df = 2201)	0.139 (df = 2199)
F Statistic	$12.071^{***}$ (df = 7; 2205)	10.829*** (df = 11; 2201)	10.348*** (df = 13; 2199

Table 5: Pooled OLS Regression of Musical Novelty on CMS Launch, Divided by Organizational Structure

	I	Dependent variable: Novelty Ind	ndex		
	(1)	(2)	(3)		
Program Launch	-0.004	-0.001	0.007		
	(0.024)	(0.024)	(0.025)		
Indie	0.074**	0.064**	0.066**		
(Baseline: Major)	(0.023)	(0.023)	(0.023)		
Program Launch ×	-0.079**	$-0.085^{**}$	-0.082**		
Indie	(0.027)	(0.027)	(0.027)		
Self-Releasing	0.038	0.019	0.024		
	(0.022)	(0.022)	(0.023)		
Program Launch ×	-0.011	-0.014	-0.018		
Self-Releasing	(0.025)	(0.025)	(0.025)		
Market Dominance		-0.051***	-0.045***		
		(0.009)	(0.010)		
Identity: Pop		0.030**	0.029**		
(Baseline: Hip-Hop)		(0.010)	(0.010)		
Identity: Rock		0.029**	0.025*		
		(0.011)	(0.011)		
Identity: Folk		0.078***	0.072***		
		(0.011)	(0.011)		
Newcomer		0.007	0.003		
		(0.009)	(0.009)		
Performer/Composer			0.029***		
			(0.008)		
Group Musician			-0.006		
			(0.007)		
Constant	0.391***	0.374***	0.347***		
	(0.021)	(0.023)	(0.025)		
Observations	2,213	2,213	2,213		
$\mathbb{R}^2$	0.025	0.058	0.063		
Adjusted R <sup>2</sup>	0.023	0.054	0.058		
Residual Std. Error	0.142 (df = 2207)	0.139 (df = 2202)	0.139 (df = 2200)		
F Statistic	11.443*** (df = 5; 2207)	13.552*** (df = 10; 2202)	12.410*** (df = 12; 220		

\*p<0.05; \*\*p<0.01; \*\*\*p<0.001

Table 6: Pooled OLS Regression of Musical Novelty on CMS Launch, Divided by Veteran Status

	D	ependent variable: Novelty Inc	ex.		
	(1)	(2)	(3)		
Program Launch	-0.048***	-0.038***	-0.029**		
	(0.009)	(0.009)	(0.009)		
Newcomer	0.018*	0.012	0.007		
	(0.009)	(0.009)	(0.009)		
Market Dominance		-0.047***	-0.042***		
		(0.009)	(0.010)		
Identity: Pop		0.026*	0.025*		
(Baseline: Hip-Hop)		(0.010)	(0.010)		
Identity: Rock		0.020	0.016		
		(0.011)	(0.011)		
Identity: Folk		0.075***	0.069***		
		(0.011)	(0.011)		
Indie		0.008	0.011		
(Baseline: Major)		(0.012)	(0.012)		
Self-Releasing		0.008	0.010		
		(0.011)	(0.011)		
Performer/Composer			0.033***		
			(0.008)		
Group Musician			-0.004		
			(0.007)		
Constant	0.438***	0.403***	0.373***		
	(0.005)	(0.015)	(0.017)		
Observations	2,213	2,213	2,213		
$\mathbb{R}^2$	0.014	0.048	0.055		
Adjusted R <sup>2</sup>	0.013	0.044	0.050		
Residual Std. Error	0.142 (df = 2210)	0.140 (df = 2204)	0.140 (df = 2202)		
F Statistic	15.867*** (df = 2; 2210)	13.739*** (df = 8; 2204)	12.730*** (df = 10; 2202)		

\*p<0.05; \*\*p<0.01; \*\*\*p<0.001

Table 7: Pooled OLS Regression of Musical Novelty on CMS Launch, Divided by Veteran Status Intersecting with Other Producer Types

				Depe	Dependent variable: Novelty Index	velty Index			
	V	Against Market Position	ition	V	Against Producer Identity	lentity	Again	Against Organizational Structure	Structure
	(1)	(2)	(3)	(4)	(5)	(9)	(7)	(8)	(6)
Program Launch	-0.046*** (0.010)	-0.038*** (0.010)	-0.030** (0.010)	-0.001 (0.028)	-0.009 (0.028)	-0.001 (0.028)	(0.027)	-0.013 (0.027)	-0.006 (0.027)
Newcomer	0.018 (0.009)	0.014 (0.009)	0.009	0.004 (0.023)	0.006 (0.023)	0.009 (0.023)	0.044 (0.022)	0.027 (0.022)	0.026 (0.022)
Market Dominance	-0.034* (0.016)	-0.043** (0.016)	-0.041* (0.016)		-0.043 *** (0.009)	-0.038*** (0.010)		-0.049*** (0.009)	-0.043*** (0.010)
Program Launch $ imes$ Market Dominance	0.001 (0.025)	0.001 (0.026)	0.005 (0.025)						
Newcomer $ imes$ Market Dominance	-0.013 (0.023)	-0.010 (0.023)	-0.009 (0.023)						
Identity: Pop (Baseline: Hip-Hop)		0.026*	0.025*	0.059**	0.053*	0.056** (0.021)		0.031**	0.030**
Identity: Rock		0.021 (0.011)	0.016 (0.011)	0.054*	0.045 (0.023)	0.047*		0.029**	0.025*
Identity: Folk		0.075 ***	0.069***	0.074***	0.073**	0.076***		0.077***	0.071***
Program Launch $ imes$ Pop				-0.082** (0.031)	-0.067* (0.031)	-0.062* (0.031)			
Program Launch $ imes$ Rock				-0.004 (0.035)	0.002 (0.035)	-0.001 (0.035)			
Program Launch $ imes$ Folk				0.021 (0.036)	0.038 (0.036)	0.026 (0.037)			
Newcomer $\times$ Pop				0.047	0.040 (0.026)	0.029 (0.026)			
Newcomer $\times$ Rock				-0.046 (0.029)	-0.041 (0.029)	-0.050 (0.029)			

	* ({	<b>S</b>	*08	<u> </u>	04 7)	41 3)	** ({	07 ')	** (5	(df = p<0.001
	0.067**	0.025 (0.023)	$-0.080^{*}$ (0.031)	0.011 (0.030)	-0.004 (0.027)	-0.041 (0.025)	0.029***	_0.007 (0.007)	0.346***	2,213 0.065 0.059 = 0.139 2198)
	0.064**	0.020 (0.022)	-0.085** (0.031)	0.013 (0.030)	-0.001 (0.027)	-0.037 (0.025)			0.373***	2,213 2,213 0.065 0.065 0.055 0.059 0.139 (df = 0.139 (df = 2200) *p<0.05; **p<0.01; ***p<0.001
	0.074**	0.038	-0.071* (0.031)	0.025 (0.030)	-0.014 (0.027)	-0.056* (0.025)			0.391*** (0.021)	2,213 0,029 0,025 0,141 (df = 2204)
-0.037 (0.032)	0.015 (0.012)	0.010 (0.011)					0.030***	-0.002 (0.007)	0.350*** (0.024)	2,213 0.064 0.058 0.139 (df = 2196)
-0.035 (0.032)	0.013 (0.012)	0.009 (0.011)							0.381*** (0.023)	2,213 0.059 0.053 0.139 (df = 2198)
-0.025 (0.032)									0.381***	2,213 0.048 0.043 0.140 (df = 2201)
	0.012 (0.012)	0.010 (0.012)					0.033***	-0.004	0.372***	2,213 0.055 0.050 0.140 (df = 2200)
	0.008 (0.012)	0.008 (0.012)							0.402*** (0.015)	2,213 0.048 0.043 0.140 (df = 2202)
									0.442***	2,213 0.023 0.021 0.021 0.142 (df = 2207)
Newcomer $\times$ Folk	Indie (Baseline: Major)	Self-Releasing	Program Launch $ imes$ Indie	Program Launch $ imes$ Self-Releasing	Newcomer $ imes$ Indie	Newcomer $ imes$ Self-Releasing	Performer/Composer	Group Musician	Constant	Observations R <sup>2</sup> Adjusted R <sup>2</sup> Residual Std. Error

# 3 Figures

#### 3.1 Musician Service

Below is a screenshot of the Musician Service launched by a Chinese Music Streaming Platform. The monthly revenue generated from the songs on the platform is presented at the top of the interface. A detailed breakdown of the revenue is also given, including revenue coming from advertisements, subscriptions, digital albums, and streams. The line chart at the bottom illustrates the revenue generated in the past seven days, the past month, or the past year, contingent upon choosing.

我的收入 6997.08 1070.75 10月税前收入 1.0万 2223.51 总收入 广告分成 会员包 数字专辑 点播 10月税前收入 ¥10291.34 近30日 近1年 在曲线图上移动手指, 可查看每日新增收入 (元)

Figure 1: Musician Service Interface

Source: https://www.cr173.com/Guide/356275\_1.html (retrieved on March 03, 2022)

### 3.2 New releases breakdown

Below is a bar chart that presents the detailed breakdown of the new releases by market position, producer identity, and organizational structure. Thre graphic suggests that the monetization program remarkably attracted more self-released titles, as well as Pop songs, which helped expand the market and enrich the supply end. Together with Figure 2 in the main article, the graphic shows a clear external impact of the monetization program on the market in terms of disrupting the status quo, substantiating the existence of an external shock and identifying its influence on the platform.

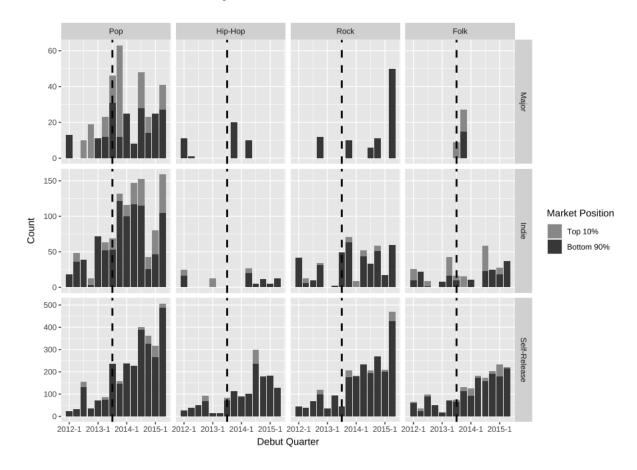


Figure 2: Breakdown of new releases