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Firm markups and the economic value of innovation ☆

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ABSTRACT

We examine the relationship between firms' markups and the economic value of their innovation, including both the private value captured by the innovating firm and the knowledge spillovers that benefit other firms. Using a sample of over 14,500 EU firms and 2,400 US firms granted patents between 2005 and 2014, we find that innovation by high-markup firms is more valuable privately and also creates more external value. These associations are robust to controlling for the stock of past innovation and to estimating innovation value in various ways.

1. Introduction

The large literature on how market structure affects innovation highlights two opposing forces: On the one hand, firms with significant market power may innovate more because they find it easier to recoup their R&D investments, consistent with Schumpeter (1942)'s hypothesis that monopoly rents can fund innovation and reward risk-taking. On the other hand, entrenched incumbents may be reluctant to replace profitable existing products, supporting the Arrow (1962) perspective that greater competitive pressure spurs "escape-competition" innovation. Later theories often reconcile these views by showing that the effect of market power on innovation can be positive, negative, or even nonlinear, depending on appropriability conditions, technological opportunities, and the threat of entry (e.g., Gilbert and Newbery, 1982; Aghion et al., 2005; Hashmi, 2013).

Empirically, many studies find that firms with higher market power or industry concentration—measured, for instance, by the Lerner index, markups, or HHIs—innovate more, in line with Schumpeter's scale-based argument (e.g., Lerner, 1934; Hall, 1988; Romer, 1990). Others point to an inverted-U relationship, observing that while moderate market power may promote innovation, very high levels can undermine it by reducing firms' incentives to replace profitable legacy technologies (e.g., Bresnahan and Reiss, 1991; Aghion et al., 2005; Hashmi, 2013). Still others find an overall negative association, especially when competition shocks spur productivity gains and patenting (e.g., Okada, 2005; Bloom et al., 2016a). In this extensive work, existing studies often rely on input-

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based proxies for innovation returns, typically focusing on R&D spending, patent counts, or industry-level outcomes.[1] The empirical literature has paid less attention to how market power relates to the value of knowledge spillovers from innovation, which is essential for understanding the broader social returns to market power. Our paper goes some way to filling these two gaps by analyzing markups together with new output-based measures of innovations' private and spillover values.

We revisit the firm-level relationship between market power, in the form of markups, and innovation incentives, using the newly developed innovation values in Guillard et al. (2021) (GMMTV). This approach allows us to show how markups are correlated with firms' profits from their innovations and also with the broader knowledge externalities that accrue to other inventors. By exploiting these rich measures, we can shed new light on whether high-markup firms generate innovations with higher social value.

In a sample of almost 17 thousand innovating EU and US firms that were granted patents between 2005 and 2014, we find a positive relationship between markups and the economic value of innovation at the firm-year level. That is, the most valuable innovation is done by firms earning high markups over their marginal costs of production. This finding is present within year, and industry-country groups. Across firms and within industry-country groups, an increase of one standard deviation in firm markup is associated with innovation that is 12% more valuable. While there is some evidence that this relationship is non-monotonic, the marginal effect remains positive within our sample and is largest for firms in the third and particularly the fourth quartile of the markup distribution.

Our measure of the total economic value of a firm's innovation in a given year is the sum of the private value of its patented innovations and the value of spillovers created when those patents are used as inputs to subsequent innovation. There is a positive correlation of 0.78 between our measures of the log of private and spillover values at the firm-year level. That is, innovations that are privately valuable also generate larger knowledge externalities.[2] The fact that this correlation is not perfect raises the question of whether high markup firms generate more spillovers as well as more privately valuable innovation.

When we look at each component separately, we find that both are positively and significantly associated with current firm-level markups. While the magnitude of the marginal relationship with private values is similar to that for total economic value, an increase of one standard deviation in firm markup is associated with spillover values that are 9% higher within year and industry-country group. This relationship continues to hold when controlling for a firm's private innovation value. In other words, high markup firms contribute more to future knowledge generation independent of their private gains from innovating.

We measure firm markups using the method set out in the appendix of Aghion et al. (2023) (ABMR), which builds on Forlani et al. (2023).[3] Their measure is described as a firm-level Lerner index that can be interpreted as markups in excess of returns to scale. They argue that this definition captures firm-level market power better than estimates of markup over marginal cost as it allows firms some compensation for increasing returns.

One of our contributions is in the firm-year-level measurement of the value of innovation. GGMTV constructs estimates of the private and spillover value created by a large, global set of patented inventions. To measure private value, they rely on information in patents to predict and extrapolate abnormal stock market returns around the day of a patent grant. They then use the global patent citation network to assign a portion of the private value created by any patent as spillovers emanating from prior patents. Their intuition is that the value of a knowledge spillover of one patent is a portion of the private value captured by innovations by other firms that directly or indirectly build on it. In this paper, we aggregate across innovations to value the private and spillover value created by the innovations patented by each firm in each year.

While the association between firm innovation value and markups in a given year does not establish a causal relationship in either direction, we use the panel nature of our data to ask whether the stock of past innovation is an omitted firm-level variable associated with both current markups and innovation. The large literature on market concentration and markups shows that both have been increasing in recent decades, see De Loecker et al. (2020), with ambiguous welfare implications. On the one hand, higher industry concentration could have been motivated by firms' incentives to exercise market power and charge higher prices, all else equal, lowering welfare (Gutiérrez and Philippon, 2017). On the other, technological change leading to higher returns to large fixed cost investments, lowering marginal production costs, could be driving both industry concentration and higher observed markups, and increasing welfare.[4] This second mechanism is modeled in De Ridder (2024), who relates high markups and reduced market entry to incumbent firms' past investments in intangible assets.[5]

While the markup estimates we use adjust for firm-level increasing returns to scale and quasi-fixed production factors, they do not explicitly include a firm's stock of patents as an input to production, see Aghion et al. (2023).[6] These mechanisms suggest there will be a positive relationship between a firm's stock of past innovation activity and its current markup. Because innovative activity is also likely persistent at the firm level, this variable will also be positively correlated with current innovation.

We construct the initial value of a firm's past innovation by summing the private value it created in all years prior to the start of the markup sample data period, depreciating each past year's contribution by the number of years since the innovation took

[1] Key papers in this empirical literature are summarized in more detail in the table in Appendix A.

[2] The spillovers we measure are limited to the knowledge externalities arising when innovations serve as a valuable input to subsequent innovation and do not measure the impact of innovation on consumer surplus. GMMTV includes some discussion and extensions to consumer surplus considerations.

[3] While ABMR focuses only on firms in or related to the automotive industry, and Forlani et al. (2023) looks only at Belgium, our sample includes all patenting fields and a large number of EU countries as well as the US. Mosquera (2023) describes the sample in more detail.

[4] Recent papers have shown that there is limited evidence that higher markups are associated with higher prices, e.g. (Conlon et al., 2023; Miller, 2025).

[5] Cassiman and Vanormelingen (2013) shows that firms' markups are related to both their product and process innovations.

[6] In addition to the papers cited above estimating returns to innovation and market power, there is a long tradition of estimating the contribution of R&D expenditures or outputs in the production function, (Hall et al., 2005, 2010; Bloom et al., 2013; Doraszelski and Jaumandreu, 2013).

place. We include this variable as a control in the baseline regressions and find it serves to reduce the magnitude of the association between markups and innovation values by around half. In other words, variation in past innovative activity at the firm level is positively correlated with current markups and innovation but a one standard deviation higher markup remains associated with 7% more valuable innovation, and 6% more valuable knowledge spillovers after taking account of this firm-level initial characteristic.

We undertake a series of robustness tests using different measures of total, private and spillover innovation value. Of particular relevance is that we recompute private innovation values for the subset of EU firms that are publicly listed during the sample. This gives us the direct abnormal market returns to patent grants for these firms and does not rely on an extrapolation of KPSS values from similar US firm innovations. While this is a smaller sample, the results remain strong and the magnitude of the association between markup and private innovation value is much larger. We then show that the results are robust to measuring private innovation value with traditional measures of patent quality: forward citations, and the family size of the documents submitted for protection across different legal jurisdictions. An alternative way of measuring spillovers that does not rely on private values but only on the network of citation counts, unweighted by private values, also gives similar results. Finally, decomposing firm-year innovation values into the number of innovations and the mean value of innovations shows high markup firms innovate more on the extensive and intensive margins.

Overall, our results show that firms with higher market power today are producing the most valuable innovations, consistent with current monopoly rents playing a role in incentivizing breakthrough technological advances. The majority of these rents accrue privately to the firms, but innovations by high-markup firms also create valuable knowledge spillovers for future innovation. When viewed in the context of the large theoretical literature on competition and innovation, the results suggest a need for dynamic considerations when considering welfare effects of market power.

Section 2 describes the sample of innovating firms and describes how we construct the variables used in the study. Section 3 sets out the estimation equations relating innovation value to current markups and then presents the results. Section 4 discusses the endogeneity of firm markups and explores firm-level factors. Section 5 presents robustness analysis. Section 6 concludes and suggests some avenues for future work.

2. Data

This section describes the firm-year panel data we use. We build on GMMTV to measure total private and spillover values created by a firm each year and build on ABMR to derive firm markups from data available in ORBIS and Compustat. The sample includes 14,681 firms from across 23 EU countries and 2,415 US firms. Each has some patenting activity from 2005 to 2014 and has financial accounts available in ORBIS or Compustat. Around 75% of the EU firm-year observations are from firms in Italy, France, and Germany. Hence, firms from these three countries and from the US dominate the sample.[7]

Obtaining legal protection of the monopoly rights over an innovation in multiple countries requires multiple patent applications to different patent authorities.[8] GMMTV construct a patent database including over 15 million patented innovations between 2005 to 2014 by aggregating all the information available about any single innovation from all of the patent authorities.[9] The sample used in this paper consists of more than 760,000 innovations with a first patent filing done by firms in our sample between 2005 and 2014.

We assign firms to an industry using the 2-digit NACE Revision 2 codes in ORBIS for the European sample. For the US sample, we convert NAICS codes to NACE codes manually. For manufacturing, we use 3-digit NAICS codes, while for other sectors we use the 2-digit codes. Fig. 1 shows the distribution of firms by industry. Top industries in the sample are *Machinery and equipment*, *Computer, electronic, and optical products*, and *Fabricated metal products*.[10] In our analyses, we use variation within industry or within industry-country to examine the relationship between markups and innovation value.

In an alternative specification, we use technology field fixed effects, rather than industry fixed effects. We assign each innovation in the GMMTV subsample to 35 technological fields using the classification in Schmoch (2008), based on the International Patent Classification (IPC) codes present in PATSTAT. To aggregate this to the level of the firm, we place each firm in the technological field where it most actively patents during the data period, taking a random field in case of a tied first place. The fields most frequently observed in the data relate to engineering and machine-related technologies.

In GMMTV, the whole sample of patents, as well as the network of citations that link them together, is used to map out knowledge flows from any one patent (Jaffe et al., 1993), and then value those flows.[11] An innovation generates knowledge spillovers when the patents associated with that innovation are cited by subsequent innovations: that is, when an innovation is a knowledge input to a future innovation production function. Both direct and indirect spillovers are traced through the network of patent citations using a recursive approach similar to Google's PageRank algorithm.

[7] Our sample is determined by data availability of the appropriate input measures for markups. It is more representative of firms from EU countries with good coverage in ORBIS and of large, listed US firms in Compustat.

[8] These include the United States Patent and Trademark Office (USPTO), the European Patent Office (EPO), and the Japanese Patent Office (JPO).

[9] An innovation is defined at the patent family level rather than the individual patent level. This avoids issues arising from inventions that result in multiple, nearly identical patents due to filings across jurisdictions.

[10] The figure shows the 29 industries with most firms in our sample, and combines all other industries in the category *Other industries combined*, which has about 10 percent of the sample firms.

[11] In GMMTV, the estimates of private value are used to parameterize a structural model of innovation incentives to infer the social returns of a subsidy to R&D activity, by technology field.

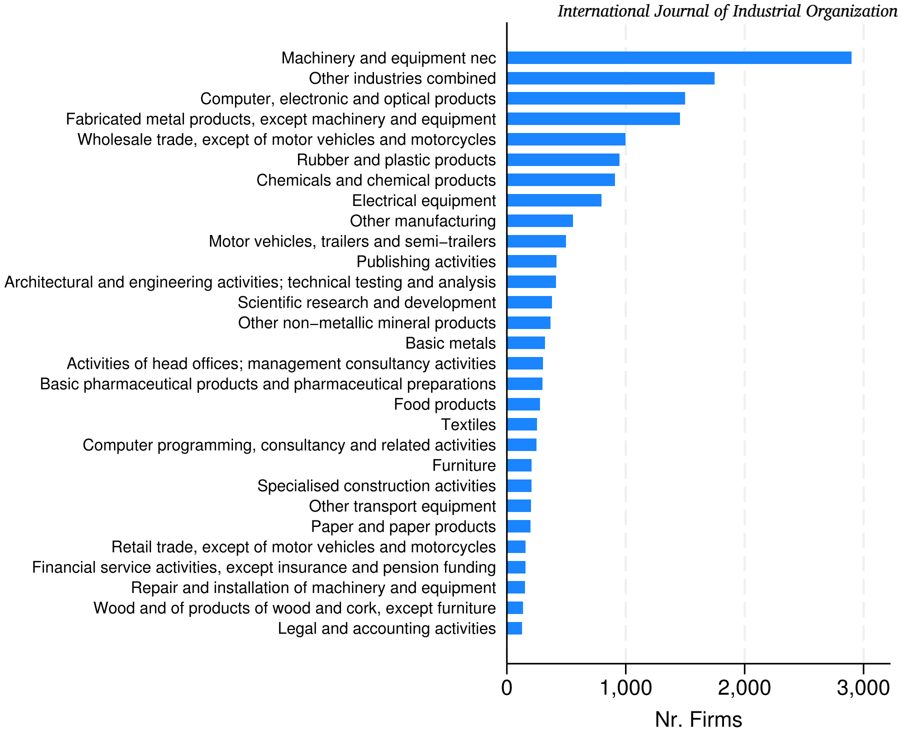

Fig. 1. Firm distribution by industry.

The value of knowledge spillovers is a share of the private value captured by subsequent innovators when their patents are granted.[12] Hence, estimating the spillovers generated by any one patent requires measures of the private value of all of the innovations that cite that patent, directly and indirectly. GGMTV construct these measures using data on the private values of the subset of all innovations derived in (Kogan et al., 2017) (KPSS). These data come from an event study that captures abnormal stock market returns around the grant date for patents held by publicly listed U.S. firms. It gives measures for approximately 3.4% of all global patent families.[13]

GMMTV extend their measures to all patented innovations using a binning approach similar to hedonic regressions. They group patents based on filing year, technology classification, patent family size, and claim count, assigning an expected private value to each bin using the average stock-market-based estimate from patents within the same bin.[14] The correlation between the KPSS and GMMTV measures for the sample that has direct stock-market based measure is around 0.51, indicating that the patent-based predictors in combination capture a great deal of information present in stock market event studies.[15]

This process yields estimates of innovation-level private values for all innovations in the GMMTV data, and can be aggregated by country, field, or year to illustrate across-group variation. In this paper, we aggregate private values to the firm-year level. To link firms to their patents, we rely on the ORBIS IP dataset, which matches applicant names to ORBIS firms, eliminating the need to disambiguate applicant names.[16]

We aggregate the private value of innovations i patented by firm f in year t:

$$PV_{ft} = \sum_{i \in I_{ft}} PV_i. \tag{1}$$

Here, I_{ft} denotes the set of all innovations patented by firm f in year t.[17] Around 47,000 firm-year observations have non-zero values of PV_{ft}. A firm-year observation equals zero if the firm has no patents in the relevant year. Firm-year observations of zero are in the sample if the firm has at least one privately valuable innovation in other years.

[12] The share can be interpreted as being derived from the innovation production function coefficient on knowledge inputs.

[13] We deflate the returns to 2014 values.

[14] If a bin contains fewer than 10 stock-market-based value estimates, they iteratively relax bin definitions until each patent receives a private value estimate.

[15] It is important to note that the KPSS measure incorporates stock market variations due to news unrelated to the patent grant. As a result, it embodies a great deal of "white noise" that we should not expect to be correlated to patent-based indicators of value.

[16] Patent offices do not assign a consistent firm identifier across patents, meaning that variations in spelling result in separate entity records.

[17] In constructing PV_{ft}, we also produce a firm-year measure of the mean private value of innovations as well as the number of innovations. We use these variables in later robustness analysis.

Table 1
Summary statistics.

	Mean	Std. Dev.	Min.	25th	50th	75th	Max.
Markup	1.28	0.84	0.02	0.98	1.11	1.30	35.44
log(V)	1.47	2.04	0.00	0.00	0.00	3.08	11.51
log(PV)	1.40	1.99	0.00	0.00	0.00	2.97	11.26
log(SV)	0.55	1.21	0.00	0.00	0.00	0.25	10.37
log(PV stock t = 0)	2.71	2.57	0.00	0.00	2.87	4.63	13.21
log(Fam. size)	0.94	1.42	0.00	0.00	0.00	1.61	9.52
log(Citations)	0.61	1.30	0.00	0.00	0.00	0.69	10.94
log(SV with PV = 1)	0.17	0.54	0.00	0.00	0.00	0.04	7.79
N	115279						

Number of firms: 17096 | Logs refer to natural logarithm of variable plus 1.

The other component of total innovation value that we measure and analyze is knowledge spillover value. This is the externality arising from the fact that the knowledge embodied in an invention is, once public, imperfectly excludable, meaning that it serves as a valuable input to the R&D of other firms. The core idea of GMMTV's measure is that the value of a knowledge spillover is captured in private returns reaped by other firms. Hence, the spillover value of one invention in that knowledge stock is defined as its marginal contribution to the value of follow-on inventions.

Compared to the standard approach in the literature, which measures knowledge spillovers by counting forward citations, the GMMTV approach has two advantages. First, it accounts for indirect citations—that is, it captures spillovers to innovations that build indirectly on a given innovation's knowledge—providing a more comprehensive measure of spillovers. Second, it weights citations by their private value, recognizing that spurring valuable future innovations generates higher spillovers than inducing low-value innovations. In a validation exercise, GMMTV show that these differences matter. Forward citation counts and their spillover value measure are only weakly correlated, and university patents—which are expected to generate relatively high spillovers—are overrepresented among patents with high spillover values (SV), regardless of their forward citation counts. Conversely, university patents are underrepresented among patents with low SV, even when those patents receive many forward citations.

We aggregate the spillover value of innovations i patented by firm f in year t:

$$SV_{ft} = \sum_{i \in I_{ft}} SV_i. \tag{2}$$

GMMTV derive an expression for the total value of an innovation i, which is the sum of its private value and spillover value as:

$$V_i = PV_i + SV_i = PV_i + \sigma \sum_{j \in F_i} \frac{1}{N_j} V_j, \tag{3}$$

where j indexes any innovation in the set of innovations F_j citing innovation i, whereas N_j counts the number of innovations that are cited by j. This expression defines a system of equations—one equation for each innovation i—that effectively assigns a portion of the private value of each innovation as spillovers derived from directly and indirectly cited innovations. Solving this system iteratively with an algorithm GMMTV call P-Rank yields an expression for SV_i for each innovation in the citation network. We note that the measures of SV_i used to construct firm-year-level measures of spillovers for the innovations in our data include the direct and indirect spillovers throughout the entire GMMTV network of over 15 million innovations and not only those innovations that appear directly in our sample.

We take logs of $(V_{ft} + 1)$, and summarize this variable in the first row of Table 1. The mean value of $log(V_{ft} + 1)$ is 1.47, which corresponds to a mean value of 107 million CPI-adjusted 2014 US dollars. The mean number of innovations per firm-year is 6.63. For the $47,744$ observations of V_{ft} that are non-zero the mean innovation value is 17.6 million.

The second row of Table 1 summarizes the log of one plus the private value of innovation. This tends to make up the majority of an innovation's total economic value. The log of innovation spillover values, $(SV_{ft} + 1)$, is summarized in the third row of the table. Fewer firm-year innovations generate positive spillover values than have positive private values. This is the case whenever a firm has no patents in a year or when the patents it has have zero forward citations within the sample period. We find that $30,939$ of the firm-year observations have positive spillover values, meaning that around two thirds of all privately-valuable innovations generate some knowledge externalities.

Firm-year-level markups are estimated following the methodology of Forlani et al. (2023), as applied in Aghion et al. (2023). They use a production function framework explicitly allowing for price variation between firms.[18] Markups are computed as the ratio of the output elasticity of material inputs to the share of material expenditure in total revenue. This methodology accounts for firm-level heterogeneity in productivity, demand, and pricing power, distinguishing between true total factor productivity (TFP) and revenue-based productivity measures. It sets out a translog production function that describes a firm's log revenue growth in terms of the growth in flexible factors, labor and materials, a quasi-fixed production factor, capital, a Hicks-neutral shifter of TFP or demand, and an average firm-level markup over marginal cost. This gives an output elasticity term contributing to the markup that varies

[18] This is similar to the approach suggested in De Loecker and Warzynski (2012).

at the firm-year level, reflecting complementarities between the firm's inputs. Estimating the production function allows for scaling markup estimates for firm-level returns to scale.[19]

The framework is applied to firm-level production data, using revenue, employment, wage cost shares, input usage, and cost shares from ORBIS to recover markups across firms. This variable is summarized in the last row of Table 1 for our sample of 115,279 firm-year observations.

3. Firm-level innovation value and markups

3.1. Empirical framework

To investigate the relationship between firm markups and the value of firm innovation, we take logs of $(V_{ft}+1)$, where V_{ft} is as defined in equation (3) and summarized in Table 1. We then estimate regressions of the form:

$$log(V_{ft}+1) = \alpha + \beta\mu_{ft} + \gamma_t + \gamma_c + \gamma_j + \epsilon_{ft}, \tag{4}$$

where μ_{ft} is the firm-year level markup, and ϵ_{ft} is the error term. Equation (4) includes various fixed effects, for the year, t, the country where the firm is located, c, the firm's NACE Revision 2 two-digit industry, j, and the interaction of country and industry. In each estimation throughout the paper, standard errors are clustered at the firm level.

In each estimation specification of equation (4), the coefficient β can be interpreted as the semi elasticity of a firm's innovation value with respect to its markup in that year, that is, as the percentage change in the economic value of a firm's innovation for a one unit increase in its markup. As shown in Table 1, the standard deviation in markups in the data is 0.84, so a one standard deviation increase is associated with a percentage increase in the value of innovation that is 84% of the magnitude of the estimated coefficients.

Motivated by the results in the prior literature (e.g., Aghion et al., 2005), we also explore whether this relationship is non-monotonic by estimating the quadratic specification,

$$log(V_{ft}+1) = \alpha + \beta_1\mu_{ft} + \beta_2\mu_{ft}^2 + \gamma_t + \gamma_c + \gamma_j + \epsilon_{ft}, \tag{5}$$

and a quartile regression, of the form,

$$\log PV_{ft} = \alpha + \beta_2\mu_{2,ft} + \beta_3\mu_{3,ft} + \beta_4\mu_{4,ft} + \gamma_t + \gamma_c + \gamma_j + \epsilon_{ft+\epsilon_{ft}}, \tag{6}$$

where β_2, β_3, and β_4 in equation (6) measure the effect of being in the second, third, or fourth quartile of the markup distribution relative to the omitted first quartile.

We decompose the total economic value of firm-year innovation into the private value and spillover value, as shown in equation (3). To investigate the relationship between each component and markup, we replace the dependent variable $log(V_{ft}+1)$ in equations (4), (5), and (6) with $log(PV_{ft}+1)$ and $log(SV_{ft}+1)$.

3.2. Results

Table 2 presents the results from estimating equation (4) and finds a positive relationship between a firm's markup and the economic value of its innovation in the same year. Column 2 includes year fixed effects. On average, across countries and technology fields and within year, firms with a one standard deviation higher markup produce innovation output that is around 29% more valuable.[20]

Column 3 of Table 2 adds fixed effects to control for average variation across two-digit industries, assigning a fixed effect to a firm based on its ORBIS classification. In this case, the coefficient falls slightly, so that a one standard deviation increase in markup is associated with 24% more valuable innovation. Column 4 includes country-year fixed effects, reducing the size of the estimated coefficient to around one half of the value in column 3, which suggests that much of the variation across markups in the data can be attributed to the firm's location country. However, even within country, a one standard deviation increase in markup is associated with 13% more valuable innovation. Column 5 includes the interaction of industry and country fixed effects and shows that the relationship between markups and innovation value is similar within these groups.

Table 3 presents the results from estimating equation (5), with the same set of fixed effects across columns as in Table 2. It shows there is evidence of the non-monotonic relationship between markup and innovation value shown in Aghion et al. (2005). The positive coefficient on markups and the negative coefficient on markups squared suggest an inverted-U whereby innovation incentives are increasing in markups at low markup levels but diminishing as markups increase.

Table 4 presents the results from estimating equation (6). It shows that the positive association in Table B.1 is present in the third and particularly in the fourth quartile of the markup distribution. The value of innovation by firms with markups in the fourth quartile of the markup distribution is around 12% higher than the innovation produced by firms in the first quartile, within year and country-industry groups. These results together with those in Table 3 imply that the range of firm markups in the data remains to the left of the inflection point in the non-monotonic relationship so that incentives for innovation are always increasing with markup in our sample.

[19] The approach is described in detail in Aghion et al. (2023), online appendix, Section C3.

[20] The results throughout the paper are robust to winsorizing the dependent variables.

Table 2
Total value and markups.

log(V)	(1)	(2)	(3)	(4)	(5)
Markup	0.35***	0.35***	0.29***	0.15***	0.16***
	(0.024)	(0.024)	(0.023)	(0.022)	(0.023)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq.	0.021	0.022	0.070	0.086	0.15
N	115279	115279	115279	115279	115267
Mean V	106.84	106.84	106.84	106.84	106.84
Mean Markup	1.28	1.28	1.28	1.28	1.28

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3
Total value and markups.

log(V)	(1)	(2)	(3)	(4)	(5)
Markup	0.57***	0.57***	0.47***	0.23***	0.23***
	(0.032)	(0.032)	(0.031)	(0.031)	(0.032)
Markup^2	-0.020***	-0.020***	-0.015***	-0.0068***	-0.0057***
	(0.0019)	(0.0019)	(0.0019)	(0.0016)	(0.0017)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq.	0.025	0.026	0.072	0.087	0.15
N	115279	115279	115279	115279	115267
Mean V	106.84	106.84	106.84	106.84	106.84
Mean Markup	1.28	1.28	1.28	1.28	1.28

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4
Total value and markups.

log(V)	(1)	(2)	(3)	(4)	(5)
Markup 2nd quart.	-0.021	-0.022	0.034	0.054**	0.045*
	(0.025)	(0.025)	(0.025)	(0.024)	(0.024)
Markup 3rd quart.	0.094***	0.094***	0.13***	0.087***	0.064**
	(0.028)	(0.028)	(0.028)	(0.027)	(0.026)
Markup 4th quart.	0.59***	0.59***	0.47***	0.22***	0.14***
	(0.036)	(0.036)	(0.033)	(0.032)	(0.031)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq	0.015	0.016	0.065	0.084	0.15
N	115279	115279	115279	115279	115267
Mean V	106.84	106.84	106.84	106.84	106.84
Mean Markup	1.28	1.28	1.28	1.28	1.28

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B presents results replacing total economic value, V_{ft}, in equation (4) with private economic value, PV_{ft}. The results show that firms with the highest markups also have the most privately valuable innovations.

Turning to the knowledge spillovers from firm-year-level innovation, Table 5 shows the results of estimating equation (4) replacing the dependent variable with $log(SV_{ft} + 1)$, the log of the value of knowledge spillovers to future innovations. Columns 1 and 2 show that there is a significant positive association. A one standard deviation in firm markups is associated with 22% more valuable spillovers. Columns 3, 4, and 5 add fixed effects for the mean spillover value created by firms in a given industry, country, or within country-industry groups. The coefficients are smaller than for total economic value, but a one standard deviation in markups is

Table 5
Spillover value and markups.

log(SV)	(1)	(2)	(3)	(4)	(5)
Markup	0.26***	0.26***	0.20***	0.11***	0.11***
	(0.019)	(0.018)	(0.017)	(0.017)	(0.017)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq.	0.033	0.081	0.13	0.16	0.22
N	115279	115279	115279	115279	115267
Mean SV	17.21	17.21	17.21	17.21	17.21
Mean Markup	1.28	1.28	1.28	1.28	1.28

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6
Spillover value and markups.

log(SV)	(1)	(2)	(3)	(4)	(5)
Markup	0.44***	0.42***	0.34***	0.18***	0.18***
	(0.024)	(0.024)	(0.022)	(0.022)	(0.022)
Markup^2	-0.016***	-0.015***	-0.012***	-0.0060***	-0.0052***
	(0.0014)	(0.0013)	(0.0012)	(0.00098)	(0.0010)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq.	0.041	0.088	0.14	0.16	0.22
N	115279	115279	115279	115279	115267
Mean SV	17.21	17.21	17.21	17.21	17.21
Mean Markup	1.28	1.28	1.28	1.28	1.28

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7
Spillover value and markups.

log(SV)	(1)	(2)	(3)	(4)	(5)
Markup 2nd quart.	-0.0058	-0.024*	0.012	0.022*	0.020
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Markup 3rd quart.	0.026*	0.011	0.037**	0.013	0.0072
	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)
Markup 4th quart.	0.41***	0.39***	0.29***	0.13***	0.082***
	(0.023)	(0.023)	(0.020)	(0.019)	(0.017)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq	0.022	0.070	0.13	0.16	0.21
N	115279	115279	115279	115279	115267
Mean SV	17.21	17.21	17.21	17.21	17.21
Mean Markup	1.28	1.28	1.28	1.28	1.28

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

associated with a 9% increase in knowledge spillovers within country-industry. These results show that there is broader social value from the innovations generated by high markup firms.

Tables 6 and 7 confirm that there is evidence of a non-monotonic relationship between markups and social innovation value but that the highest quartile of markups in the sample are still associated with 7% higher knowledge spillovers within country and industry.

Finally in this section, we ask whether there is a marginal association between markups and spillover value after accounting for the correlation between innovation's private and spillover values. To do this, we focus on the more than 47,000 firm-year observations

Table 8
Spillover value and markups conditional on private value.

log(SV mean)	(1)	(2)	(3)	(4)	(5)
Markup	0.12***	0.11***	0.064***	0.039***	0.022***
	(0.0093)	(0.0075)	(0.0055)	(0.0053)	(0.0049)
log(PV mean)	0.072***	0.11***	0.10***	0.11***	0.10***
	(0.0034)	(0.0031)	(0.0029)	(0.0030)	(0.0029)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq	0.042	0.33	0.37	0.40	0.43
N	47744	47744	47742	47743	47616

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

where there firms have at least one innovation. We regress the mean spillover value per innovation, $log(SV_{ft}mean)$, on markups controlling for the mean private value, $log(PV_{ft}mean)$, in equation (4). The results in Table 8 show that there is a positive marginal association within country-industry group. A one standard deviation in markups is associated with 2% higher knowledge spillovers controlling for private values. That is, controlling for the fact that the firms with the highest markups produce the highest private value innovations, these firms are also generating proportionally greater innovation spillover values.

The results in this section provide robust evidence that the firms with higher markups in our sample generate more valuable innovations, even after accounting for differences across countries, industries, and over time. The estimated relationship between markups and innovation value remains positive and statistically significant across all specifications, although its magnitude varies with the inclusion of various fixed effects. The fact that industry-level fixed effects account for a substantial portion of the observed variation suggests that market conditions play an important role in shaping the relationship between firm market power and innovation incentives. However, even within industry-country groups, firms with higher markups continue to produce more valuable innovations. Similar patterns emerge when considering spillover values separately, reinforcing the idea that high-markup firms contribute to broader knowledge diffusion. These firms' innovations are more privately valuable but are also those that generate the greatest external value.

4. Discussion of mechanisms

The relationships in the previous section are not necessarily causal, merely a positive association between markups and innovation values in a given year and we do not have any data that isolates exogenous variation in firm markups allowing for identification. To discuss the plausible mechanisms that underlie the associations, we first note that there is very little relationship within firm. That is, variation over time in a firm's markup is not related to variation in its contemporaneous innovation activity. This suggests that non-time-varying firm-level factors play a prominent role in the overall findings.

The literature offers several theoretical mechanisms that can have led to across-firm variation in markups. An exogenous increase in market concentration arising from industry-level factors (Autor et al., 2017) enables productive firms to charge prices that include higher markups over marginal costs. One such industry-level factor is technological progress that alters the nature of production to include more fixed and fewer variable inputs, which also lowers marginal production costs. If industry-level technical change is embodied in firms' patents, then a firm's stock of patents can potentially affect its markups via both higher prices or lower marginal costs.

These channels suggest that a firm's past innovation activity is an omitted variable in equation (4). We use our data to construct the stock of past innovation value, S_{f0}, in the year prior to the first time firm appears in the regressions. While the markup sample goes from 2005 to 2014, the innovation-level value measures go back to 1995. We compute the value of the innovation stock at the firm level in 2005 as follows:

$$S_{f,2005} = \Sigma_{\tau=1995}^{\tau=2005} \delta PV_{f\tau},$$

and assume a depreciation rate, δ, of 0.15.[21] We take logs of $S_{f,2005} + 1$, which gives the variable summarized in the fourth row of Table 1. We then include this non-time varying variable as a firm-level control in equation (4), with both total economic value and spillover value as the firm-year level outcomes.

Table 9 presents the results that include the control for the value of a firm's initial innovation stock. As expected, this control is positively correlated with the value of current innovation, showing that some firms in the data are persistent innovators. We can compare the magnitudes of the coefficients on markups to those in the baseline specification in Table 2. The within-industry-country coefficient in column 5 has fallen from 0.16 to 0.084, suggesting that around half of the association between markups and innovation value is due to those innovative firms also being firms that tend to have high markups. Nonetheless, after controlling for this firm-level factor a one-standard deviation in markup is associated with a 7% more valuable current innovation.

[21] Estimates of the depreciation rate of knowledge vary quite widely in the literature, ranging from below 10 percent up to 30 percent (Hall, 2007; De Rassenfosse and Jaffe, 2017). We take 15 percent as our baseline depreciation rate. Varying the rate between 0 and 50 percent does not change our conclusions.

Table 9
Total value and markups, controlling for initial innovation stock.

log(V)	(1)	(2)	(3)	(4)	(5)
Markup	0.15***	0.15***	0.12***	0.077***	0.084***
	(0.015)	(0.015)	(0.015)	(0.016)	(0.017)
log(PV stock t = 0)	0.44***	0.44***	0.42***	0.42***	0.40***
	(0.0055)	(0.0055)	(0.0055)	(0.0056)	(0.0057)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq.	0.32	0.32	0.32	0.32	0.34
N	115279	115279	115279	115279	115267
Mean V	106.84	106.84	106.84	106.84	106.84
Mean Markup	1.28	1.28	1.28	1.28	1.28

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10
Spillover value and markups, controlling for initial innovation stock.

log(SV)	(1)	(2)	(3)	(4)	(5)
Markup	0.15***	0.15***	0.11***	0.068***	0.070***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.014)
log(PV stock t = 0)	0.24***	0.24***	0.23***	0.22***	0.22***
	(0.0046)	(0.0046)	(0.0045)	(0.0045)	(0.0045)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq.	0.28	0.32	0.34	0.35	0.38
N	115279	115279	115279	115279	115267
Mean SV	17.21	17.21	17.21	17.21	17.21
Mean Markup	1.28	1.28	1.28	1.28	1.28

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For spillover values, the estimates in Table 10 can be compared to those in Table 5. Firms with valuable past innovation tend to generate more innovation spillovers as well as more privately valuable innovation. Controlling for this firm-level factor, a one standard deviation increase in firm markups is associated with 6% more valuable knowledge spillovers.

5. Robustness to alternative innovation value measures

In this section, we evaluate the robustness of the associations shown in prior sections to using a range of different measures of total, private, and spillover innovation values.

Our measure of both private and spillover value relies on the extrapolation exercise in GMMTV, which models KPSS's stock-market-based measure using patent-level predictors. GMMTV show that these predictors—and therefore their measure—explain a large share of the variation in KPSS values. However, it is unclear whether the predictors capture all relevant variation. Moreover, if the relationship between patent indicators and private values differs between U.S. listed firms and other firms in our sample, the resulting measure could be biased. To address these concerns, we assess the robustness of our results using an alternative, more direct measure of private value.

Our first approach extends the KPSS measure to as many firms in our dataset as possible. We use daily stock returns from Compustat North America and Compustat Global, firm-level data from ORBIS, and patent data from PATSTAT and ORBIS IP. We link Compustat-listed firms to ORBIS entities using ISIN and CUSIP identifiers, and match them to patent applications and grant dates via ORBIS IP and PATSTAT. With daily stock returns and shares outstanding,[22] we replicate the KPSS event study design and re-calculate our private value measure for the subset of firms and patents for which this is feasible.

As shown in Table 11, the positive relationship between markups and total private value persists with this direct measure. Within country and industry, a one standard deviation increase in markups is associated with a 36 percent increase in innovation value. While this sample includes larger firms with higher markups and is not directly comparable to the baseline, the result supports the robustness of our main conclusion.

[22] Variable cshoc in Compustat.

Table 11
Total Value based on country-specific stock markets and markups.

log(KPSS extended)	(1)	(2)	(3)	(4)	(5)
Markup	0.68***	0.66***	0.61***	0.34***	0.43***
	(0.080)	(0.080)	(0.085)	(0.082)	(0.088)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq.	0.011	0.023	0.062	0.050	0.12
N	26667	26667	26666	26667	26661
Mean KPSS extended	3.79e+08	3.79e+08	3.79e+08	3.79e+08	3.79e+08
Mean Markup	1.59	1.59	1.59	1.59	1.59

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12
Innovation forward citation count and markups.

log(Citations)	(1)	(2)	(3)	(4)	(5)
Markup	0.28***	0.28***	0.22***	0.10***	0.12***
	(0.020)	(0.020)	(0.018)	(0.017)	(0.018)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq.	0.034	0.079	0.14	0.18	0.24
N	115279	115279	115279	115279	115267
Mean Citations	0.10	0.10	0.10	0.10	0.10
Mean Markup	1.28	1.28	1.28	1.28	1.28

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13
Innovation document family size and markups.

log(Fam. size)	(1)	(2)	(3)	(4)	(5)
Markup	0.23***	0.23***	0.20***	0.098***	0.11***
	(0.017)	(0.017)	(0.017)	(0.016)	(0.017)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq.	0.018	0.019	0.072	0.078	0.15
N	115279	115279	115279	115279	115267
Mean Fam. size	22.21	22.21	22.21	22.21	22.21
Mean Markup	1.28	1.28	1.28	1.28	1.28

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the long empirical literature measuring patent quality, the number of forward citations a patent receives has long been viewed as informative (Jaffe, 1986). Later work has also used data on the number of documents submitted in relation to a given innovation across legal jurisdictions, counting the size of the document family (Putnam, 1996; Harhoff et al., 2003). GMMTV collects both these variables at the innovation level, using the former to construct the global citation network and the latter to group innovations into bins for the purposes of assigning private values.

In Tables 12 and 13, we replace the GMMTV measure of total economic value at the firm level in equation (4) with these two widely-used innovation characteristics, aggregated to the firm-year level. Both these proxies for private innovation value are associated with higher markups, as in the baseline results.

We also investigate robustness to an alternative measure of spillovers. We use the same iterative method to trace out direct and indirect forward citations as in GMMTV, but set the private value of each innovation to one. This approach generates the spillovers of an innovation based on its influence on the quantity of future innovations without considering the value of those spillovers. Table 14 replaces SV_{ft} in Table 5 with this version of spillovers. The coefficients remain positive and significant and slightly smaller in magnitude than in Table 5, suggesting that high markup firms generate a larger quantity of spillovers and those spillovers are also more valuable.

Table 14
Alternative spillover measure and markups.

log(SV with PV = 0)	(1)	(2)	(3)	(4)	(5)
Markup	0.11*** (0.0099)	0.11*** (0.0098)	0.084*** (0.0092)	0.045*** (0.0092)	0.051*** (0.0097)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq.	0.029	0.059	0.11	0.13	0.19
N	115279	115279	115279	115279	115267
Mean evconstantpv	1.32	1.32	1.32	1.32	1.32
Mean Markup	1.28	1.28	1.28	1.28	1.28

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15
Number of innovations and markups.

log(Innovations)	(1)	(2)	(3)	(4)	(5)
Markup	0.16*** (0.013)	0.16*** (0.013)	0.14*** (0.013)	0.064*** (0.013)	0.076*** (0.013)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq.	0.019	0.020	0.078	0.088	0.16
N	115279	115279	115279	115279	115267
Nr. innovations	6.63	6.63	6.63	6.63	6.63
Mean Markup	1.28	1.28	1.28	1.28	1.28

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16
Mean innovation value and markups.

log(V mean)	(1)	(2)	(3)	(4)	(5)
Markup	0.12*** (0.0073)	0.12*** (0.0072)	0.074*** (0.0061)	0.062*** (0.0061)	0.036*** (0.0055)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq.	0.012	0.018	0.064	0.061	0.12
N	47744	47744	47742	47743	47616
Avg. V mean	17.57	17.57	17.56	17.57	17.56
Mean Markup	1.37	1.37	1.37	1.37	1.37

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Finally, in this robustness section, we return to the GMMTV measure of innovation value and address the fact that when aggregating to the firm-year level, we combine variation in the number of innovations a firm patents and the mean value of those patents. By decomposing these two parts, we learn whether high markup firms are innovating more on the extensive margin or intensive margin.

Table 15 looks at the relationship between markups and the count of firm-year innovations. Table 16 considers the smaller sample of firm-years with at least one innovation and shows how the mean value of the innovations varies with markups. These findings show that higher markup firms both innovate more frequently and generate more valuable innovations.

6. Conclusion

This paper contributes to the long-standing debate on the relationship between market power and innovation by providing firm-level evidence that higher markups are associated with producing more valuable innovations. Using a large dataset of patenting US and EU firms, we find that firms with higher markups generate innovations that are not only more valuable to the innovating firm but that also produce greater knowledge spillovers, which amplifies their broader economic impact. While this relationship follows an inverted-U shape, the firms with the highest markups generate the most valuable innovations in the markup range in the sample, consistent with monopoly rents playing an important role in financing technological advances.

Taken together, these findings suggest that policymakers weighing the costs and benefits of market power should consider not only its static effects on pricing and consumer welfare but also its dynamic association with innovation. Our results show that high-markup firms are at the forefront of generating both private and socially valuable innovations. Future research could extend this analysis by exploring the roles played by firm-specific factors—such as managerial strategies, investment in intangible assets, or access to financial resources—in explaining why some high-markup firms innovate more than others.

CRediT authorship contribution statement

Ralf Martin: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jenniffer Solorzano Mosquera:** Data curation, Formal analysis, Methodology. **Catherine Thomas:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Dennis Verhoeven:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Appendix A. Overview of key studies on market power and innovation

Study	Type	Market Power Measure	Innovation Measure	Data	Main Finding
Schumpeter (1942)	Theory				**Positive**: Firms with market power have stronger incentives to innovate.
Arrow (1962)	Theory				**Negative**: Market leaders have weaker incentives due to the “replacement effect.”
Dasgupta and Stiglitz (1980)	Theory / industry-level	Number of firms in R&D race (competition intensity)	R&D investment, innovation speed		**Mixed**: More firms can increase total innovation but also cause wasteful duplication.
Gilbert and Newbery (1982)	Theory (incumbent vs. entrant)	Market structure (incumbent vs. entrant)	Preemptive patenting, innovation timing		**Positive (under threat)**: Incumbents innovate to deter entry.
Reinganum (1983)	Theoretical (dynamic competition)	Market structure (leader vs. challenger)	R&D effort, innovation timing		**Varies (stochastic)**: Innovation incentives depend on uncertainty.
Scherer (1967)	Industry-level (cross-sectional)	Concentration ratio (4-firm, etc.)	R&D intensity, patent counts	1950s–1960s; US industry data	**Inverted-U**: Innovation peaks at moderate market power.
Cohen and Levin (1989)	Industry and firm-level	Various (concentration, market share, etc.)	Various (R&D, patents, etc.)	1960s–1980s; Meta-analysis	**No universal monotonic**: Market power explains little once industry effects are controlled.
Nickell (1996)	Firm-level panel	Competition index (e.g., price-cost margin)	Productivity growth (TFP)	1972–1986; UK firms panel data	**Negative**: More competition increases productivity growth.
Blundell et al. (1999)	Firm-level panel	Firm: market share; Industry: competition intensity	Patent counts, Tobin’s Q	1972–1982; UK manufacturing firms	**Mixed**: Higher market share spurs innovation, but competition also stimulates it.
Aghion et al. (2005)	Industry-level panel	Lerner Index (price-cost margin)	Patent citations	1973–1994; UK manufacturing	**Inverted-U**: Innovation is highest at moderate market power.
Hashmi (2013)	Industry-firm panel	Lerner index / markups	Patent citations	1970–2000; US manufacturing	**Positive**: More market power correlates with higher innovation.
Bloom et al. (2016b)	Firm /industry panel	Import competition (China shock)	Patents, R&D, TFP	1996–2007; EU firms + trade data	**Negative**: Increased competition from China led to more innovation.
Gutiérrez and Philippon (2017)	Industry-level, macro approach	Concentration ratios, profit margins	R&D investment intensity	1990s–2010s; US & EU industry data	**Negative**: Rising concentration linked to lower R&D investment.

Appendix B. Firm markups and innovation private values

This appendix shows the results when replacing the dependent variable in equation (4) with private innovation value, that is, the part of total economic value that is captured directly by the innovating firm (proxied by the stock market returns earned from very similar innovations, as described in Section 2.). The relationship between private value and innovation are very similar to those for total economic value. That is, there is a positive relationship between a firm’s markup and the private value of its innovation in the same year.

Table B.1
Private value and markups.

log(PV)	(1)	(2)	(3)	(4)	(5)
Markup	0.33***	0.33***	0.28***	0.15***	0.16***
	(0.023)	(0.023)	(0.022)	(0.021)	(0.022)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq.	0.020	0.020	0.066	0.081	0.14
N	115279	115279	115279	115279	115267
Mean PV	89.63	89.63	89.63	89.63	89.63
Mean Markup	1.28	1.28	1.28	1.28	1.28

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2
Private value and markups.

log(PV)	(1)	(2)	(3)	(4)	(5)
Markup	0.53***	0.53***	0.44***	0.22***	0.22***
	(0.031)	(0.031)	(0.031)	(0.030)	(0.031)
Markup^2	-0.018***	-0.018***	-0.014***	-0.0062***	-0.0053***
	(0.0019)	(0.0019)	(0.0018)	(0.0016)	(0.0017)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq.	0.023	0.024	0.068	0.082	0.14
N	115279	115279	115279	115279	115267
Mean PV	89.63	89.63	89.63	89.63	89.63
Mean Markup	1.28	1.28	1.28	1.28	1.28

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3
Private value and markups.

log(PV)	(1)	(2)	(3)	(4)	(5)
Markup 2nd quart.	-0.021	-0.019	0.035	0.054**	0.045*
	(0.024)	(0.024)	(0.024)	(0.024)	(0.023)
Markup 3rd quart.	0.096***	0.097***	0.14***	0.088***	0.068***
	(0.027)	(0.027)	(0.027)	(0.026)	(0.026)
Markup 4th quart.	0.55***	0.55***	0.45***	0.21***	0.14***
	(0.035)	(0.035)	(0.033)	(0.032)	(0.030)
Year FE		✓	✓	✓	✓
Industry FE			✓		
Country FE				✓	
Industry x Country FE					✓
R-sq	0.014	0.015	0.062	0.079	0.14
N	115279	115279	115279	115279	115267
Mean PV	89.63	89.63	89.63	89.63	89.63
Mean Markup	1.28	1.28	1.28	1.28	1.28

Notes: Standard errors are reported in parentheses and clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.1 shows that there is a positive relationship between a firm's markup and the private value of its innovation in the same year that is very similar to its relationship with total economic value. A one standard deviation higher firm markup is associated with innovation output that is again around 13% more privately valuable for the innovating firm, within year, and country-industry group.

Tables B.2 and B.3 show evidence of a non-monotonic relationship between markup and private innovation value. However, in the range of markups in the data, firms generating the highest private value from innovating in a given year tend to be those with high markups.

Data availability

We can make the innovations value data available. The markups variable requires access to ORBIS, owned by Moody's, that we accessed under a license.

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