ONLINE APPENDIX:
Technological Uniqueness and Firm Performance

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Appendix A1: Codebook and Data Sources

Table A01: Variable Definitions

Variables	Descriptions	Data Sources
Number of firms in industry	Number of firms in the 6-digit GICS industry.	Compustat
Adjusted Coverage	The number of analysts covering the firm divided by the number of analysts covering the industry.	IBES
Advertising Intensity	The ratio of the firm's advertising expenditure to total operating expense.	Compustat
Analyst Attention	The number of analysts covering the firm.	IBES
Analyst Coverage Dummy	A dummy variable that is equal to 1 if the firm is covered by an analyst.	IBES
Analyst Coverage Loss	The negative of the number of analysts covering the firm.	IBES
Analyst Effort	The negative of the number of other firms that the analyst is covering	IBES
Assets (log)	Natural log of the firm’s total assets.	Compustat
Average HHI	The firm's average industry concentration measure based on weighted-sales across the firm's product market segments.	Compustat Segments
Average market share	The firm's average market share based on weighted-sales across the firm's product market segments.	Compustat Segments
Competitive Shock	Dollar value of patent shocks by peers in "atypical" industry technology classes.	KPSS2017
Cost of Capital 1	Cost of Capital based on Claus and Thomas (2001)	Claus and Thomas (2001)
Cost of Capital 2	Cost of Capital based on Easton (2004)	Easton (2004)
Cost of Capital 3	Cost of Capital based on Gebhardt et al. (2001)	Gebhardt et al. (2001)
Cost of Capital 4	Cost of Capital based on Ohlson and Juettner-Nauroth (2005)	Ohlson and Juettner-Nauroth (2005)
Dummy variable *Segment 1*	Dummy variable that is equal to 1 if the firm has sales in only a single product market segment.	Compustat Segments
Dummy variable *Segment 2*	Dummy variable that is equal to 1 if the firm has sales in exactly two product market segments.	Compustat Segments
Dummy variable *Segment 3*	Dummy variable that is equal to 1 if the firm has sales in exactly three product market segments.	Compustat Segments
Dummy variable *Segment 4*	Dummy variable that is equal to 1 if the firm has sales in more than four product market segments.	Compustat Segments
Earnings Coef. of Variation	Earnings Coefficient of Variation that is the standard deviation of the firm's earnings divided by average earnings over the last 3 years.	Compustat
Industry Centroid	Industry Centroid Technology Uniqueness measure based on a 6-digit GICS industry classification.	KPSS2017
Intangible Assets	The ratio of intangible assets to total assets.	Compustat

Knowledge Spillover Shock	Dollar value of patent shocks by peers in commonly cited technology classes.	KPSS2017
Market-Book	The ratio of the market value of equity to book value of equity for the firm.	Compustat
Number of Shareholders (log)	Natural log of the number of outstanding shares.	Compustat
Profitability	The ratio of the firm's operating income before depreciation minus total interest and related expenses minus total income taxes paid to total assets.	Compustat
R&D Intensity	The ratio of the firm's R&D expenditure to total operating expense.	Compustat
Return	Annual stock return for the fiscal year.	CRSP
ROA	The ratio of the firm's income before extraordinary items to total assets.	Compustat
Sales ($) (log)	Natural log of the firm's sales.	Compustat
Sales Growth (1-year)	The growth of the firm's sales over the past year.	Compustat
Sales Growth (past three years)	The growth of the firm's sales over the past three years.	Compustat
Share Turnover (log)	Total shares traded in the year divided by shares outstanding.	Compustat
Technology Uniqueness (standardized)	Technological Uniqueness Measure- Computed using patent shares, then standardized.	KPSS2017
Tobin's Q	The ratio of the firm's market value of assets to book value of assets.	Compustat
Stock Volatility	Standard deviation of the firm's stock price.	CRSP

Appendix A2: Different Industry Classifications

In the main text, our baseline uniqueness measure is computed based on the patenting portfolio of the firm, relative to the average patenting portfolio of the industry. The baseline results assume an industry classification based on the 6-digit GIC value of the GIND classification. This classification results in 33 unique industries. While the uniqueness measure is computed by measuring the distance between the firm's patenting portfolio vector and the industry's average patenting portfolio vector, then scaled by the number of industry categories, the number of actual partitions should not matter.

However, since the industry's average patent portfolio depends on both the industry's constituents and how they patent, one concern can be that smaller industry classifications bias firms towards being more unique since it may be easier to stand out amongst a smaller pool of peers. Hence, to ensure that our performance results are not driven by industry classification, we provide a robustness check by showing that our results hold across a variety of different industry definitions. In Table A2, we show that our results hold for alternative classifications as well, the 4-digit GGROUP in Panel A, the 8-digit GSUBIND in Panel B, and 4-digit SIC in Panel C. The alternative industry classifications result in 16 industries for the GGROUP classification, 73 industries for the GSUBIND classification, and 94 for the SIC classification.

Table A2: Different Industry Classifications

PANEL A. GGROUP (4-digit)

Variable (end of prior fiscal year)	Sales Growth	Tobin's Q	Profitability	ROA
	OLS	OLS	OLS	OLS
Models	(1)	(2)	(3)	(4)
Technology Uniqueness	0.0235***	0.0663***	0.00885***	0.00915***
	(0.00617)	(0.0233)	(0.00228)	(0.00260)
Additional Controls/FE		See Table Notes		
R-squared	0.0787	0.0552	0.180	0.121
Observations	23,050	23,050	23,050	23,050

PANEL B. GSUBIND (8-digit)

Variable (end of prior fiscal year)	Sales Growth	Tobin's Q	Profitability	ROA
	OLS	OLS	OLS	OLS
Models	(1)	(2)	(3)	(4)
Technology Uniqueness	0.0187***	0.0416***	0.00924***	0.00952***
	(0.00424)	(0.0154)	(0.00156)	(0.00186)
Additional Controls/FE		See Table Notes		
R-squared	0.0803	0.0550	0.186	0.125
Observations	22,410	22,410	22,410	22,410

PANEL C. SIC (4-Digit)

Variable (end of prior fiscal year)	Sales Growth	Tobin's Q	Profitability	ROA
	OLS	OLS	OLS	OLS
Models	(1)	(2)	(3)	(4)
Technology Uniqueness	0.0155***	0.0245	0.00630***	0.00651***
	(0.00502)	(0.0187)	(0.00173)	(0.00215)
Additional Controls/FE		See Table Notes		
R-squared	0.0851	0.0546	0.210	0.143
Observations	18,503	18,503	18,503	18,503

Notes: Technological uniqueness is measured as the normalized distance from the average industry patent portfolio. Sample is restricted to only include patenting firms. Controls include the log number of shareholders, log sales, sales growth (past 3 years), coefficient of variation of earnings, number of firms in the industry, dummies for firms with 2, 3, 4+ business segments, average market share across segment industries, average Herfindahl index across industries of segments, R&D intensity, advertising intensity, and intangibles as fraction of assets. Additional fixed effects include firm fixed effects, industry-by-year fixed effects, and region-by-year fixed effects where the industry-by-year fixed effects is either the 4-digit GGROUP in panel A, 8-digit GUBSIND in panel B, or 4-digit SIC in panel C multiplied by the year. Standard errors are clustered at the firm level and are reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Appendix A3: Disaggregation Level of Patent Classes used for Technological Uniqueness

Since a firm's relative uniqueness may also be affected by how the technology classes themselves are defined, an additional robustness check that is performed is by redefining patent technology classes using the first 4 alpha-numeric digits of the patent's CPC as opposed to the baseline classification using the first 3 alpha-numeric digits of the patent's CPC. This definition of patent technology classes increases the number of unique technology classes from 129 classes to 665 unique classes.

In Table A3, we show that this alternative patent class decomposition has no qualitative impact on our OLS performance results.

Table A3: Patent Class Decomposition (4-digit Technology Classes)

Variable (end of prior fiscal year)	Sales Growth	Tobin's Q	Profitability	ROA
	OLS	OLS	OLS	OLS
Models	(1)	(2)	(3)	(4)
Technology Uniqueness (4-class)	0.0335***	0.115***	0.0107***	0.00999***
	(0.00665)	(0.0293)	(0.00252)	(0.00275)
Number of Shareholders (log)	-0.0727***	0.461***	-0.0364***	-0.0331***
	(0.00916)	(0.0443)	(0.00403)	(0.00470)
Sales (log)	0.155***	-0.222***	0.0882***	0.0743***
	(0.0105)	(0.0369)	(0.00476)	(0.00501)
Sales Growth (past three years)	-0.266***	0.417***	0.0341***	0.0244**
	(0.0306)	(0.0932)	(0.00931)	(0.0112)
CV Earnings	-0.00131	-0.0239***	-0.00159***	-0.00134***
	(0.00111)	(0.00368)	(0.000392)	(0.000469)
Number of Industry Firms	-0.0000947	0.000648	-0.0000140	-0.0000223
	(0.0000955)	(0.000443)	(0.0000390)	(0.0000414)
Business segments: 2	0.000274	-0.239***	-0.0102	-0.0125
	(0.0184)	(0.0704)	(0.00649)	(0.00802)
Business segments: 3	-0.0304	-0.237***	-0.0316***	-0.0337***
	(0.0203)	(0.0794)	(0.00766)	(0.00922)
Business segments: 4 or more	-0.0205	-0.249***	-0.0342***	-0.0361***
	(0.0211)	(0.0777)	(0.00762)	(0.00937)
MMCI	0.0681	0.288	-0.0156	-0.0351
	(0.0509)	(0.186)	(0.0195)	(0.0216)
Average Market Share	-0.124*	0.0690	-0.0818***	-0.0756***
	(0.0674)	(0.218)	(0.0209)	(0.0240)
R&D intensity	-0.161*	0.00453	-0.160***	-0.315***
	(0.0828)	(0.281)	(0.0298)	(0.0358)
Advertising intensity	0.325	0.664	-0.260*	-0.383**
	(0.288)	(1.454)	(0.135)	(0.153)
Intangibles/assets	0.184***	-1.749***	-0.0613***	-0.109***
	(0.0398)	(0.160)	(0.0151)	(0.0168)
Firm FE	YES	YES	YES	YES
Industry-by-Year FE	YES	YES	YES	YES
Region-by-Year FE	YES	YES	YES	YES
R-squared	0.0789	0.0559	0.180	0.121
Observations	23,050	23,050	23,050	23,050

Notes: Technological uniqueness is measured as the normalized distance from the average industry patent portfolio, with patent classes measured using 4-digit technology classes. There are 665 unique technology classes using this 4-digit class system. Sample is restricted to only include patenting firms. Average market share measures sales-weighted market share of firm across all its business segments. MMCI is sales-weighted average of industry concentration (Herfindahl index) across all business segments the firm is active in. Standard errors are clustered at the firm level and are reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Appendix A4: Patent Class Weighting – Detailed Example

Since Jan 1st, 2013, the USPTO began transitioning from the United States Patent Classification (USPC) system to the Cooperative Patent Classification (CPC) system, a joint effort by the European Patent Office (EPO) and USPTO to "harmonize" their classification systems into a single hierarchal system having similar structure to the International Patent Classification (IPC). By 2015, the USPTO was exclusively classifying using the CPC system only and the USPC classes were no longer being updated.[1]

The stated goal of the CPC system is to accurately classify patents, facilitating the retrieval of their technical subject matter[2] and does so using a hierarchical level organizing and naming system.[3] Table A4 Panel A is an example of a patent (#7877944) that was granted to a firm in 2011. We assign the patent to a technology class using the patent's section and class designation, or the first three alpha-numeric values of the CPC. Starting with the section designation (A, B, C, D, E, F, G, H, and Y), there are eight main trunk assignments possible (A-H), with an additional section Y reserved for new emerging and/or cross-sectional technologies. The next two digits in the CPC system determines the class assignment. For instance, from Table 1 in the main text, patent technology class F41 includes all mechanical engineering patents (section F) related to weapons and weapons-related components (class 41). In contrast, technology class F42 encompasses mechanical engineering patents (section F) specifically related to ammunition and blasting (class 42).

[1] See https://e-courses.epo.org/mod/url/view.php?id=916
[2] See https://www.uspto.gov/web/offices/pac/mpep/s905.html
[3] The CPC system classifies patents by Section-> Class -> Subclass -> Groups -> Subgroups.

Table A4: Patent Class Weighting Examples

Panel A: Patent Example

United States Patent **7,877,944**
Seidel **February 1, 2011**

Tower foundation, in particular for a wind energy turbine

Abstract

A tower, in particular for a wind energy turbine, comprises a first tower segment (18) having a wall (20) comprising concrete material and a second tower segment (26) having a wall (28) comprising steel. The wall (28) of the second tower segment (26) comprises an end portion (30) embedded in an embedent portion (32) of the wall (20) of the first tower segment (18). The second tower segment (26) within its embedded end portion (30) comprises at least one anchoring element (38, 40, 52) projecting radially from an inner or an outer surface (42, 44) or both inner and outer surfaces (42, 44) of the wall (28) of the second tower segment (26), the anchoring elements (38, 40, 52) being arranged along an axial direction of the second tower segment (26).

Panel B: Cooperative Patenting Classification (CPC) and Technology Classes

Patent Number	**CPCs**	**Kogan et al (2013)**	**Equal Weight**	**Weighted Classes**	**Majority Class**	**First Class (Kogan)**
7877944	E02D 27/42; F03D 13/22; F05B 2230/60; Y02E 10/728; Y02E 10/72; Y02P 70/50; F05B 2240/912	E02D27/42;F03D11/045;F03D13/22;F05B2230/60;F05B2240/912;Y02E10/728;Y02P70/523	E02, F03, F05, Y02	E02 (0.14), F03 (0.29), F05 (0.29) , Y02(0.29)	F03 (0.33), F05 (0.33), Y02 (0.33)	E02
7328707	A61B 17/00234; A61B 17/12022; A61B 17/3468; A61F 5/0079; A61B 2017/00557; A61B 2017/00827; A61F 2/0036; A61F 2/20; Y10S 128/25	A61B17/00234;A61B17/12022;A61B17/3468;A61B2017/00557;A61B2017/00827;A61F2/0036;A61F2/20;A61F5/0079; Y10S128/25	A61, Y10	A61 (0.89), Y10(0.11)	A61	A61
8477817	H01S 5/12; B82Y 20/00; H01S 5/34306 ; H01S 5/1231; H01S 5/3406; H01S 5/209	B82Y20/00;H01S5/12;H01S5/1231;H01S5/209;H01S5/3406;H01S5/34306	B82, H01	B82 (0.17), H01 (0.83)	H01 (5)	B82
7059778	G02B 6/4298; G03F 7/70166; G03F 7/70075; G02B 6/06; B82Y 10/00 ; G02B 6/4249; Y10S 385/901	B82Y10/00;G02B6/06;G02B6/4249;G02B6/4298;G03F7/70075;G03F7/70166;Y10S385/901	B82, G02, G03, Y10	B82 (0.14), G02 (0.43), G03 (0.29), Y10 (0.14)	G02 (3)	B82

One issue with the new CPC system of classifying patents is that each patent can be assigned to multiple CPC designations. Our technology class definition, based on the section-class hierarchy, reduces many of these multiples, as patents with different subclasses or subgroups can still share the same section and class assignment. In our sample, using our technology class hierarchy system, approximately 60% of the patents only have one technology class assignment. This effectively means that regardless of how we classify patents with multiple CPC designations, the majority of the patents in our sample will still be unaffected by this decision. However, the remaining 40% of the patents have two or more assigned technology classes, with the mean/median number of technology classes per patent equal to two.[4] In the following below, we will detail how we handle patents with multiple CPC designations.

Our patent CPC data comes from Kogan et al. (2017) (henceforth Kogan), who initially provided patent class data up to 2013 but has since extended coverage through 2020.[5] They scrape the patent's entire CPC data but their algorithm assembles the technology classes in alphabetical order, resulting in the loss of the ordering information after aggregating to our section-class hierarchy. For instance, consider patent 8988776 granted to 3M in 2015.[6] This patent involves multilayer optical films orientated in specific directions to reflect and transmit light. By our technology class definition, this patent is assigned to the following technology classes: G02, B32, and Y10. Technology class G02 encompasses technological systems involving optics, B32 involves layered products, and Y10 includes new technologies of multi-layered products of different thicknesses. Using the Kogan dataset, B32 is presented as the first technology class as it is ordered first alphabetically, in contrast to Justia[7] or Google Patents[8] who lists G02 first, according to the original patent image. This can present a problem when using the Kogan dataset if the patent has multiple technology class designations and the researcher only uses the first class in the Kogan dataset. While the first class in the Kogan dataset is still a class based on a CPC assigned to the patent, it may not be the primary class as determined by the USPTO, and assuming it is may induce measurement error in the results.

[4] This CPC distribution is highly skewed though (max number of different tech classes for a patent is 24), 88% of the patents have 2 or less technology classes using the section-class classification system.
[5] See https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data
[6] https://patft.uspto.gov/netacgi/nph-Parser?Sect1=PTO1&Sect2=HITOFF&d=PALL&p=1&u=%2Fnetahtml%2FPTO%2Fsrchnum.htm&r=1&f=G&l=50&s1=8988776.PN.&OS=PN/8988776&RS=PN/8988776
[7] https://patents.justia.com/patent/8988776
[8] https://patents.google.com/patent/US8988776

Before we detail how we address the multiple CPC issue, it is worth mentioning again that this only affects 40% of patents in the sample, as the remaining 60% of patents are categorized into one technology class. The first method of categorizing patents, as presented in the main text, employs an equal weighting scheme, assuming that all technology classes receive the same weight and are equally represented, regardless of how the CPCs are ordered. The drawback to this scheme, however, is that it ignores patents with multiple classifications into the same technology class. Yet, since all technology classes are equally weighted, this reduces the likelihood of mis-categorizing the primary technology class of the patent. In Table A4 Panel B, each of the patents listed in column 1 is assigned an equal weight into the technology classes listed in column 4. This method results in no difference between using the actual CPC data and that obtained from Kogan. Consider the example of patent number 7877944 (Table A4 panel B row 2). When equal weighting is applied to the CPCs, each of the four technology classes (F02, F03, F05, and Y02) is given an equal weight of 0.25.

Appendix A5: Different Weighting Schemes for Patents with Multiple Patent Classes for Technological Uniqueness Measure

Next, we consider different weighting algorithms to factor in patents that are assigned to multiple technology classes. In Table A04 column 5 (weighted-classes), each patent is normalized by the total number of assigned technology classes, ensuring that the sum of the weights of the technology classes for each patent always adds up to 1. For patent number 7328707 in row 2 of Table A4 panel B, technology class A61 appears 8 times while Y10 appears only once. Under the weighted-class algorithm, A61 is given a technology class weight of 0.89 (8/9) while Y10 is given a technology class weight of 0.11 (1/9).

The majority class records the technology class occurs with the highest frequency. In cases where patents have multiple technology class assignments that occur with the same frequency, an equal weighting algorithm is applied. For example, in Table A4 Panel B, patent number 8477817 has technology class H01 occurring in the assigned CPCs and is thus designated as the assigned technology class.

Finally, the first-class approach is the first technology class assigned in the Kogan dataset. While this approach may incorrectly assume that a secondary technology class is the primary technology class, as observed in Table A4 Panel B for patents 8477817 and 7059778, our informal examinations indicate that this first-class approach still correctly selects the primary class 80% of the time.[9] Table A5 provides an example of how the four different measures compare.

Table A5: Comparison of Various Technology Class Assignments

Panel A: Patent Classes (Class-Weighted)

Variable (end of prior fiscal year)	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Technology Uniqueness	0.0269***	0.0695***	0.00877***	0.00958***
	(0.00658)	(0.0256)	(0.00248)	(0.00275)
Additional Controls/FE	See Table Notes			
R2	0.0793	0.0559	0.180	0.121
Observations	23,050	23,050	23,050	23,050

Panel B: Patent Classes (Majority Class)

Variable (end of prior fiscal year)	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
	OLS	OLS	OLS	OLS
Models	(1)	(2)	(3)	(4)
Technology Uniqueness	0.0252***	0.0745***	0.00879***	0.00995***
	(0.00627)	(0.0243)	(0.00238)	(0.00256)
Additional Controls/FE	See Table Notes			
R2	0.0792	0.0562	0.180	0.121
Observations	23,050	23,050	23,050	23,050

Panel C: Patent Classes (First Class)

Variable (end of prior fiscal year)	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
	OLS	OLS	OLS	OLS
Models	(1)	(2)	(3)	(4)
Technology Uniqueness	0.0304***	0.0622**	0.00746***	0.00789***
	(0.00687)	(0.0263)	(0.00275)	(0.00303)
Additional Controls/FE	See Table Notes			
R2	0.0797	0.0557	0.179	0.120
Observations	23,050	23,050	23,050	23,050

[9] This includes the 60% of all patents that has one technology class.

Notes: Technological uniqueness is measured as the normalized distance from the average industry patent portfolio (centroid). Patents are classified to the three-digit class by weighted frequency of three-digit classes in panel A, assignment to the three-digit class that occurs the most frequently (majority) in panel B, and assignment to the class that first appears in the Kogan et al. (2017) data set (first class) in panel C. Sample is restricted to only include patenting firms. Controls include the log number of shareholders, log sales, sales growth (past 3 years), coefficient of variation of earnings, number of firms in the industry, dummies for firms with 2, 3, 4+ business segments, average market share across segment industries, average Herfindahl index across industries of segments, R&D intensity, advertising intensity, and intangibles as fraction of assets. Fixed effects include firm , industry-by-year, and region-by-year fixed effects. Standard errors are clustered at the firm level. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Appendix A6: Different Rolling Windows for Technological Uniqueness Measure

Our baseline results apply a rolling three-year patent grant counting approach to minimize the impact of the uncertainty surrounding patent grants that are out of the firm's control. The choice of three-years is based on the median time it takes for a patent application to be granted in the sample. Shorter rolling periods may make firms appear more unique, as they decrease the impact of a more diverse set of patents in the firm's portfolio.

In Table A6, we apply a rolling five-year patent grant counting approach and find that our performance results continue to hold.

Table A6: Rolling 5-year Patent Grants

Variable (end of prior fiscal year)	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
	OLS	OLS	OLS	OLS
Models	(1)	(2)	(3)	(4)
Technology Uniqueness	0.0282***	0.0732**	0.00960***	0.0110***
	(0.00767)	(0.0298)	(0.00308)	(0.00341)
Sales (log)	0.167***	-0.226***	0.0878***	0.0738***
	(0.0103)	(0.0370)	(0.00471)	(0.00503)
Sales Growth (past three years)	-0.285***	0.436***	0.0292***	0.0214*
	(0.0313)	(0.0938)	(0.00974)	(0.0116)
CV Earnings	-0.00198*	-0.0240***	-0.00144***	-0.00115**
	(0.00109)	(0.00362)	(0.000393)	(0.000467)
Number of Shareholders (log)	-0.0734***	0.450***	-0.0353***	-0.0334***

	(0.00954)	(0.0429)	(0.00419)	(0.00490)
Business segments: 2	0.00526	-0.207***	-0.00986	-0.0122
	(0.0186)	(0.0707)	(0.00671)	(0.00844)
Business segments: 3	-0.0219	-0.207***	-0.0297***	-0.0321***
	(0.0209)	(0.0773)	(0.00792)	(0.00964)
Business segments: 4 or more	-0.0191	-0.242***	-0.0343***	-0.0358***
	(0.0213)	(0.0778)	(0.00788)	(0.00977)
MMCI	0.0303	0.0440	-0.0104	-0.0264
	(0.0523)	(0.179)	(0.0197)	(0.0217)
Average Market Share	-0.199***	-0.192	-0.0997***	-0.0900***
	(0.0643)	(0.191)	(0.0211)	(0.0242)
R&D intensity	-0.161*	-0.0895	-0.150***	-0.308***
	(0.0831)	(0.285)	(0.0297)	(0.0358)
Advertising intensity	0.350	1.289	-0.294**	-0.419***
	(0.288)	(1.482)	(0.144)	(0.161)
Intangibles/assets	0.184***	-1.714***	-0.0635***	-0.115***
	(0.0405)	(0.157)	(0.0160)	(0.0175)
Firm FE	YES	YES	YES	YES
Industry-by-Year FE	YES	YES	YES	YES
Region-by-Year FE	YES	YES	YES	YES
Observations	23,050	23,050	23,050	23,050

Notes: Technological uniqueness is measured as the normalized distance from the average industry patent portfolio. Sample is restricted to only include patenting firms. In this specification, we use the 5-year rolling granted patents to compute the firm's TU measure. Controls include the log number of shareholders, log sales, sales growth (past 3 years), coefficient of variation of earnings, number of firms in the industry, dummies for firms with 2, 3, 4+ business segments, average market share across segment industries, average Herfindahl index across industries of segments, R&D intensity, advertising intensity, and intangibles as fraction of assets. Fixed effects include firm fixed effects, industry-by-year fixed effects, and region-by-year fixed effects. Standard errors are clustered at the firm level. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Appendix A7: OLS with Firm, Industry and Time Fixed Effects Only

In the main text, we use a full set of firm fixed effects and industry-by-time as well as region-by-time fixed effects. This is done not only to control for a variety of differential industry and regional time trends, but also to clearly separate out the effect of changes in technological uniqueness due to changes in the innovation direction of the focal firm, compared to changes in industry trends. However, one potential concern with employing an extensive set of fixed effects is over-differencing, which can remove meaningful persistent variation. Over-differencing may result in a reduction in the signal-to-noise ratio of estimates and can introduce a strong bias in OLS results towards zero.

To address potential concerns with over-differencing, Table A7 reports our baseline OLS performance regression but only using firm fixed effects, industry fixed effects and time fixed effect. If over-differencing is an issue, then one would expect the results in Table A7 to be larger in magnitude and more statistically significant than the OLS results we report in Table 3 of the main text. As can be seen, the OLS results with the simpler set of fixed effects are indeed larger in magnitude in a quantitatively meaningful way. For example, the coefficient estimate of the regression coefficient for sales on technological uniqueness is 28% larger (2.96% instead of 2.31%), and the estimate for Tobin's Q is 46% larger (10.2% instead of 6.95%). These results reinforce the notion that our ambitious set of fixed effects are likely contributing to attenuation of OLS results, which implies that the OLS performance correlations in the main text tend to be very conservative.

Table A7: Simpler Set of Fixed Effects

Variable (end of prior fiscal year)	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
	OLS	OLS	OLS	OLS
Models	(1)	(2)	(3)	(4)
Technology Uniqueness	0.0296***	0.102***	0.00983***	0.0103***
	(0.00658)	(0.0257)	(0.00255)	(0.00285)
Number of Shareholders (log)	-0.0735***	0.458***	-0.0367***	-0.0333***
	(0.00916)	(0.0443)	(0.00402)	(0.00469)
Sales (log)	0.154***	-0.225***	0.0879***	0.0741***
	(0.0106)	(0.0369)	(0.00475)	(0.00500)
Sales Growth (past three years)	-0.264***	0.426***	0.0349***	0.0250**
	(0.0306)	(0.0935)	(0.00930)	(0.0112)
CV Earnings	-0.00138	-0.0242***	-0.00161***	-0.00135***
	(0.00112)	(0.00368)	(0.000392)	(0.000470)
Number of Industry Firms	-0.0000862	0.000677	-0.0000112	-0.0000197
	(0.0000955)	(0.000443)	(0.0000390)	(0.0000413)
Business segments: 2	0.00109	-0.236***	-0.00992	-0.0121
	(0.0184)	(0.0707)	(0.00655)	(0.00806)
Business segments: 3	-0.0295	-0.234***	-0.0313***	-0.0334***
	(0.0203)	(0.0799)	(0.00769)	(0.00925)
Business segments: 4 or more	-0.0199	-0.247***	-0.0339***	-0.0357***
	(0.0211)	(0.0782)	(0.00767)	(0.00942)
MMCI	0.0677	0.287	-0.0158	-0.0355
	(0.0508)	(0.186)	(0.0195)	(0.0216)
Average Market Share	-0.128*	0.0521	-0.0835***	-0.0773***
	(0.0678)	(0.218)	(0.0210)	(0.0241)

R&D intensity	-0.168**	-0.0176	-0.162***	-0.317***
	(0.0827)	(0.282)	(0.0297)	(0.0357)
Advertising intensity	0.331	0.686	-0.258*	-0.382**
	(0.287)	(1.454)	(0.135)	(0.153)
Intangibles/assets	0.184***	-1.748***	-0.0612***	-0.109***
	(0.0398)	(0.160)	(0.0152)	(0.0169)
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
R-squared	0.0722	0.0590	0.197	0.132
Observations	23,050	23,050	23,050	23,050

Notes: Technological uniqueness is measured as the normalized distance from the average industry patent portfolio. Sample is restricted to only include patenting firms. Controls include the log number of shareholders, log sales, sales growth (past 3 years), coefficient of variation of earnings, number of firms in the industry, dummies for firms with 2, 3, 4+ business segments, average market share across segment industries, average Herfindahl index across industries of segments, R&D intensity, advertising intensity, and intangibles as fraction of assets. Fixed effects include only firm and year fixed effects. Standard errors are clustered at the firm level. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Appendix A8 Distance to USPTO Office Instrumental Variable

To establish the causal effect of technological uniqueness on firm performance, the main text of the paper introduces three instrumental variables. The baseline IV is based on a shift-share (“Bartik”) measure that includes local industry clustering which is more likely to be exogenous. The second IV is predicted R&D expenditures based on state and federal R&D tax credits. The third IV is another Bartik-style IV constructed using expiring patent shares for each technology class at the industry level (excluding patents from the focal firm).

In Table A8, we introduce a fourth instrumental variable: the firm’s distance to the local USPTO field office. The idea is that firms in closer proximity to local field offices may be inclined to utilize USPTO local field office services. increased contact between local firms and the USPTO field office may increase awareness of new technologies, thereby increasing the likelihood of firms building upon each other. Based on this logic, we construct an annual distance measure (in miles) based on the zip-code of the firm’s headquarters to the nearest USPTO field office available to them, using a zip-to-zip distance measure.[10] Prior to 2005, the sole USPTO office was located in Arlington , VA (22202). Subsequently, in 2005, this office relocated to Alexandria, VA (22314).

[10] NBER zip-to-zip distance (https://www.nber.org/research/data/zip-code-distance-database).

Beginning in 2012, the USPTO began opening additional field offices, first in Detroit (4807) in July 2012, then in Denver in June 2014 (80294), Dallas (75202) in November 2015, and finally San Jose (95112) in October 2015. We map each firm's miles to the nearest USPTO field office based on the nearest distance office that was open at that time.

In Table A8, we show that a greater distance from the local USPTO field office is associated with increased technological uniqueness (column 1). This higher uniqueness also predicts faster sales growth, higher profitability, and increased ROA, albeit with a lower Tobin's Q.

Table A8: Distance to USPTO Office Instrumental Variable

Distance from USPTO Office IV

Variable (end of prior fiscal year)	**Technological Uniqueness**	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
	OLS	IV	IV	IV	IV
Models	(1)	(2)	(3)	(4)	(5)
Technology Uniqueness		1.315^{***}	-2.786^{***}	0.321^{***}	0.252^{***}
		(0.302)	(0.977)	(0.0680)	(0.0829)
Distance-USPTO IV	0.0646^{***}				
	(0.0143)				
Additional Controls	See Table Notes				
Fixed Effects	Firm, Industry, and Region				
Cragg-Donald F-stat	28.55				
Kleibergen-Paap p-value	0.001				
Observations	32,528	32,528	32,528	32,528	32,528

Notes: Technological uniqueness is measured as the normalized distance from the average industry patent portfolio (centroid). The Distance-to-USPTO IV is the distance in miles to the nearest open USPTO field office. Sample is restricted to only include patenting firms. Controls include the log number of shareholders, log sales, sales growth (past 3 years), coefficient of variation of earnings, number of firms in the industry, dummies for firms with 2, 3, 4+ business segments, average market share across segment industries, average Herfindahl index across industries of segments, R&D intensity, advertising intensity, and intangibles as fraction of assets. Fixed effects include firm, industry, and region fixed effects. Standard errors are clustered at the region-by-year level. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Appendix A9: Investment Patterns of Technologically Unique Firms

Much of our analysis has focused on documenting and understanding technological uniqueness as a resource and taking it as given. A potentially intriguing extension of our analysis is to view technological resources as starting point for the development and deployment of future resources and capabilities. Indeed, some work in finance, such as Sanford and Yang (2022) suggests that innovation creates growth options that can then be exercised via investments. A follow up question we can then explore is: Is technological uniqueness correlated with higher investment and if so, which types of investment are affected?

To address these questions, we use the same control variables discussed in section 3, while introducing two additional variables. First, we include Tobin's Q as control variable, as long-standing work in economics and finance has argued that it is a key predictor of investments (see Hayashi, 1982 and Abel and Eberly, 1994). Second, we add cash flow as a fraction of assets as a control variable, although there is a debate in finance whether this variable captures the influence of financial frictions (Fazzari et al., 1988) or is really a better measure of future profit opportunities than Tobin's Q (Alti, 2003).

Table A9 collects our evidence on how technological uniqueness is correlated with investment patterns. As shown in column 1, more innovative firms as measured by technological uniqueness exhibit systematically higher capital expenditures. This is consistent with the idea that technological uniqueness creates growth opportunities that can then be implemented using capital expenditures (see Sanford and Yang, 2022). However, Table A9 goes further in establishing that a variety of different investment expenditures are affected. Specifically, technologically unique firms consistently invest more in R&D, indicating their pursuit of additional innovation opportunities to exploit. Additionally, we consider SG&A as additional measures of investment in organizational capital, as argued by Ewens, Peters, and Wang (2021). Our results in column 3 of Table A9 suggest that technologically unique firms also invest more heavily in organizational capital, which is consistent with the notion that innovation requires novel organizational forms to be properly implemented.

Table A9: Investment Patterns of Technologically Unique Firms

Variable (end of prior fiscal year)	Capex/Assets	R&D intensity	SGA intensity	Advertising intensity
	OLS	OLS	OLS	OLS
	(1)	(2)	(4)	(5)
Technology Uniqueness	0.00910	0.0829*	0.0269	0.00467
	(0.00616)	(0.0494)	(0.0200)	(0.00501)
Tobin's Q	0.00502	0.0552*	0.0404***	0.00369***
	(0.00457)	(0.0327)	(0.0129)	(0.00124)
Cash Flow / Asset	-0.0542	-0.926***	-0.490***	-0.0615***
	(0.0361)	(0.235)	(0.0957)	(0.0168)
Number of Shareholders (log)	0.0275**	0.379***	-0.0107	-0.00207
	(0.0116)	(0.116)	(0.0288)	(0.00311)
Sales (log)	-0.0476***	-0.708***	-0.0382	-0.000659
	(0.0115)	(0.123)	(0.0401)	(0.00378)
Sales Growth (past three years)	-0.203***	-2.754***	-0.178*	-0.00567
	(0.0398)	(0.291)	(0.105)	(0.0143)
CV Earnings	-0.00236***	-0.0228***	-0.00196	-0.0000319
	(0.000569)	(0.00503)	(0.00144)	(0.000196)
Number of Industry Firms	-0.000333	0.00111	0.000878	-0.0000933
	(0.000405)	(0.00348)	(0.000990)	(0.000169)
Business segments: 2	0.0495**	0.177	0.0403	0.0123*
	(0.0195)	(0.142)	(0.0529)	(0.00656)
Business segments: 3	0.0611***	0.285*	0.0634	0.0117*
	(0.0203)	(0.148)	(0.0561)	(0.00632)
Business segments: 4 or more	0.0609***	0.287*	0.0857	0.00989
	(0.0224)	(0.166)	(0.0605)	(0.00635)
MMCI	-0.0571*	-0.375	0.106	-0.00685
	(0.0339)	(0.369)	(0.152)	(0.0129)
Average Market Share	0.124***	1.417***	-0.0532	0.00871
	(0.0333)	(0.302)	(0.121)	(0.0123)
Intangibles/assets	0.0657*	0.771**	0.341***	0.0151
	(0.0364)	(0.339)	(0.112)	(0.0164)
Firm FE	YES	YES	YES	YES
Industry-by-Year FE	YES	YES	YES	YES
Region-by-Year FE	YES	YES	YES	YES
R-squared	0.0294	0.0974	0.0318	0.0565
Observations	22,802	20,735	23,008	7,848

Notes: Technological uniqueness is measured as the normalized distance from the average industry patent portfolio. Sample is restricted to only include patenting firms. Controls include the log number of shareholders, log sales, sales growth (past 3 years), coefficient of variation of earnings, number of firms in the industry, dummies for firms with 2, 3, 4+ business segments, average market share across segment industries, average Herfindahl index across industries of segments, R&D intensity, advertising intensity, and intangibles as fraction of assets. Fixed effects include firm, industry-by-year, and region-by-year fixed effects. Standard errors are clustered at the firm level. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

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