Internet Appendix to
"Are foreign investors locusts? The long-term effects of foreign institutional ownership"

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Matching between USPTO and Worldscope

In this Appendix, we describe the algorithm we follow to match patent assignees of the patents awarded by the United States Patent and Trademark Office (USPTO) to firms in the Worldscope database for the January 1990–December 2010 period. Using historical data, for each firm in Worldscope, we compile the list of all names used by each firm currently and in the past (we use both “name” and “extended name” Worldscope variables). We also collect each firm’s country of incorporation. For each patent, we obtain the set of assignees listed on the patent grant publication document issued by the USPTO. For each assignee, USPTO provides assignee country of domicile and indicates its type: U.S. corporation, non-U.S. corporation, individual, government agency, or other. We require the patent to have at least one patent assignee indicated as a U.S. firm or non-U.S. firm.

In the first step of our matching algorithm, we standardize patent assignee names and Worldscope firm names using regular expression language. Our standardization focuses on three main aspects of assignee/firm names:

1. We ensure that assignee/firm name strings only contain a–z, A–Z, and 0–9 characters. That means we eliminate any diacritical marks and use only the letter. For example, we replace “â” to “a,” “ü” to “u,” “&Oacute” to “O,” “&Uuml” to “U,” “&#200” to “E.” We implement 292 such character replacements. We also remove multiple-character endings included in the firm name strings in Worldscope for reasons unrelated to firm names. For example, “- ADR,” “- CONSOLIDATED,” “- PRO FORMA”. We use 46 regular expressions to perform these removals.
2. We unify the suffixes, which typically describe the legal form of incorporation, in the assignee/firm name strings. For example, all the German suffixes for “GmbH” in any form (“G.M.B.H.,” “G. M. B. H.,” “g m b h,” “G m b H,” “G. m. b. H.,” “G m. b. H”) are changed to the same unified string “GMBH.” We process 817 suffixes according to this scheme using regular expression language. This ensures that differences between assignee and firm name strings do not arise because of cosmetic differences in firm names. To minimize the

probability of changing a non-suffix part of the firm name by mistake, this procedure is country-specific (i.e., we make the above replacements only if the respective suffix is used by firms incorporated in a country).

3. We abbreviate non-unique parts of assignee/firm names that have low relevance for matching. For example, the word "CORPORATION" appears in many firm names and hence can distinguish one firm name from another only marginally. We abbreviate it to "CORP," taking into account all likely misspellings of this word (e.g., "COPRPORATION," "CORPOIRATION," "CORPORTATION," "COROPORTION," "CORPOORATION"). Another example is Japanese "KABUSHIKI KAISHA," which we abbreviate to "KAB KSHA" using such regular expressions as "K[K]*ABUSH[IS]*KI[\.&-]*KAISH[I]*A," "KAB[UA]SHI[KN]I[\.&-]*[KH]AIS[HY]A,". In total, we abbreviate 302 terms like "CORPORATION" using 1,212 regular language expressions. This step makes unique elements of assignee/firm names longer than non-unique elements, which allows for a more efficient fuzzy-string matching procedure.

In the second step, we create a data set that includes all pairwise combinations of standardized patent assignee name strings and standardized Worldscope firm name strings. There are 156,609 standardized Worldscope firm name strings and 405,666 standardized patent assignee name strings, leading to approximately 63.5 billion pairs. We match all assignee-firm name pairs using the Bigram string comparison algorithm. The Bigram algorithm is used to compare two strings using all combinations of two consecutive characters within each string. For example, the word "Bigram" contains the Bigram as follows: "bi," "ig," "gr," "ra," and "am." We code the Bigram comparison function to return a value between zero and one, so that it counts the total number of Bigrams that are common between the two strings divided by the average number of Bigrams in the two strings. The Bigram algorithm is effective for our purposes because it is fast and good at handling misspellings and omission of characters, as well as the swapping of words in a string.

For assignee-firm name pairs with a Bigram score above 0.5, we also compute the

Levenshtein distance between the two strings. Intuitively, the Levenshtein distance between two strings is the minimum number of single-character edits (specifically, insertion, deletion, and substitution of characters) required to change one string into another. Using the Bigram score, Levenshtein distance, and the length of the two strings in the assignee-firm name pairs, we identify the closest Worldscope firm name for each patent assignee. We then decide whether each assignee is matched to a Worldscope firm or not, according to a metric that combines the Bigram score with the Levenshtein distance. We also impose a condition that the firm's country of incorporation obtained from Worldscope is the same as the assignee's country of domicile recorded in the USPTO data. These steps result in a database that uniquely links USPTO patent numbers to Worldscope firm codes.

We perform extensive checks on our standardization-matching algorithm. First, we use different thresholds for the Bigram score and the Levenshtein distance to find the closest matches. Second, we eliminate suffixes from the firm name and match on the so-called stem name, instead of standardizing the suffixes of firm names. These changes, even for rather extreme parameter values, have a limited impact on the matching outcome: assignments of less than 5% of patents in our data are affected. Last, using random subsamples of patents, we manually check the results of the standardization-matching algorithm and compute type I and type II errors. We find that both types of errors are lower than 1%.

We do not have data on the list of subsidiaries owned by Worldscope (publicly listed) firms in each year. For this reason, the patent portfolio we assign to firms in our sample might be smaller than the patent portfolio these firms effectively control. These checks on the matching procedure we discuss above partially address this concern, as the names of subsidiaries are often similar to names of their parent companies; typically, they share the unique part of the name, e.g., "SIEMENS" or "LAFARGE."

For patents awarded to Worldscope firms that are incorporated in the United States, we compare the outcome of our matching algorithm with the matching provided by the NBER Patent Data Project. We first compile a link table between firm codes in Worldscope and

GVKEYs in Compustat. Next, for Worldscope firms in our final sample with GVKEY, we compare the patent count in our data with that of the NBER Patent Data Project.

Panel A of Table IA.1 provides three examples of firms with large patent portfolios: IBM, Honeywell, and Google. The table shows that, since the NBER data set is based on patents awarded by the USPTO up to 2006, the NBER data can represent innovation output (patents filed) only up to the year 2002 due to truncation bias. In contrast, we use patent grant publication documents issued by the USPTO through the end of June 2013, which allows us to have a representative measure of innovation output over our full sample period. Panel B of Table IA.1 shows, for each year in our sample, summary statistics that compare the distribution of the counts of patents in our data with that of the NBER patent data. We find that the two distributions are comparable in the 2001–2002 period during which the NBER data are available. The last column of Panel B shows that the correlation coefficient between patent counts in our data and those in the NBER data is above 0.95 in the 2001–2002 period.

Table IA.1

Comparison to NBER patent matching

This table shows the number of patent applications with the USPTO assigned to selected firms by our matching algorithm (column "Matching") and the NBER patent data (column "NBER") by year. Panel A provides three examples of firms with large patent portfolios. Panel B provides the mean, standard deviation, and 95th percentile of the number of patents assigned by the "Matching" and the NBER algorithms by year for the sample of U.S. firms. The last column reports the correlation between the numbers of patents obtained with the two matching algorithms in the 2001–2002 period during which the NBER patent data are available.

	Panel A: Examples						*Panel B: Summary statistics*								
	IBM		Honeywell		Google		Matching				NBER				Correl.
Year	Matching	NBER	Matching	NBER	Matching	NBER	Nr. of Observ.	Mean	Standard Deviation	95th	Nr. of Observ.	Mean	Standard Deviation	95th	
2001	4,016	3,456	480	487	0	0	37,856	6.38	80.11	13	40,977	6.91	73.63	14	0.96
2002	3,547	2,361	570	501	0	0	38,057	6.85	79.25	15	34,102	6.14	59.40	14	0.95
2003	3,971	1,842	593	434	0	0	36,550	7.07	87.11	14	25,724	4.98	47.91	12	
2004	3,730	802	746	286	0	2	35,857	7.40	87.85	16	12,738	2.63	24.21	6	
2005	3,731	179	822	58	178	0	35,141	7.30	88.26	15	3,246	0.67	6.24	2	
2006	3,691	6	741	3	193	0	31,906	6.76	76.00	15	182	0.04	0.37	0	
2007	5,252	0	728	0	249	0	30,722	6.59	89.41	14					
2008	6,937	0	684	0	229	0	27,117	6.02	109.29	12					
2009	2,223	0	312	0	205	0	16,258	3.88	42.53	10					
2010	807	0	140	0	165	0	8,736	2.22	19.78	7					

Table IA.2

Reduced-form regression

This table shows results of ordinary least squares (OLS) firm-level panel regressions of long-term investment, employment, and innovation output on MSCI index membership using a sample of Worldscope nonfinancial and nonutility firms in the 2001–2010 period. *MSCI* is a dummy variable that equals one if a firm is a member of the MSCI ACWI, and zero otherwise. Regressions include the same control variables as those in Tables 3–5 (coefficients not shown). All explanatory variables are lagged by one year. The sample in Column 3 consists of firms with at least one patent applied for during the sample period. Variable definitions are provided in Table A.1 in the Appendix. Robust standard errors adjusted for country-year level clustering are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	*CAPEX+R&D*	*LABOR*	*PATENTS*
	(1)	(2)	(3)
MSCI	0.003**	0.109***	0.097***
	(0.001)	(0.013)	(0.021)
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
R^2	0.64	0.97	0.82
Number of observations	175,912	161,443	48,096

Table IA.3

Domestic institutional ownership and MSCI ACWI membership: placebo test

This table shows results of ordinary least squares (OLS) firm-level panel regressions of domestic institutional ownership on MSCI index membership using a sample of Worldscope nonfinancial and nonutility firms in the 2001–2010 period. *IO_DOM* is holdings by domestic institutions as a fraction of market capitalization. *MSCI* is a dummy variable that equals one if a firm is a member of the MSCI ACWI, and zero otherwise. All explanatory variables are lagged by one year. Variable definitions are provided in Table A.1 in the Appendix. Robust standard errors adjusted for country-year level clustering are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
MSCI	-0.062***	-0.001
	(0.008)	(0.003)
CLOSE	-0.146***	-0.051***
	(0.021)	(0.003)
FXSALES	0.021***	0.005*
	(0.003)	(0.003)
log(*SALES*)	0.045***	0.015***
	(0.007)	(0.001)
log(*CAPITAL*/*LABOR*)	0.008***	0.005***
	(0.002)	(0.001)
TOBIN_Q	0.002***	0.001***
	(0.001)	(0.000)
FCF	0.019***	0.001*
	(0.004)	(0.001)
LEVERAGE	-0.040***	-0.017***
	(0.002)	(0.002)
CASH	0.104***	0.034***
	(0.016)	(0.004)
TANGIBILITY	-0.011*	-0.024***
	(0.006)	(0.005)
Year fixed effects	Yes	Yes
Firm fixed effects	No	Yes
Industry fixed effects	Yes	No
Country fixed effects	Yes	No
R^2	0.60	0.92
Number of observations	179,125	175,912

Table IA.4

Foreign institutional ownership and innovation output: non-zero patent counts

This table shows results of ordinary least squares (OLS) and instrumental variables (IV) firm-level panel regressions of innovation output on institutional ownership using a sample of Worldscope nonfinancial and nonutility firms in the 2001–2010 period. The dependent variable is the logarithm of the number of patents applied for with the USPTO (*PATENTS*). In the IV regression, foreign institutional ownership is instrumented with *MSCI* (a dummy variable that equals one if a firm is a member of the MSCI ACWI, and zero otherwise). All explanatory variables are lagged by one year. Variable definitions are provided in Table A.1 in the Appendix. Robust standard errors adjusted for country-year level clustering are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	First stage	OLS	IV
Dependent variable	*IO_FOR*	*PATENTS*	*PATENTS*
	(1)	(2)	(3)
IO_FOR		0.392***	4.061***
		(0.146)	(1.240)
IO_DOM	-0.017***	0.214***	0.282***
	(0.004)	(0.052)	(0.074)
CLOSE	-0.018***	0.050	0.120**
	(0.004)	(0.046)	(0.053)
FXSALES	0.003	-0.011	-0.025
	(0.005)	(0.042)	(0.055)
log(*SALES*)	0.006***	0.085***	0.060***
	(0.001)	(0.010)	(0.015)
log(*CAPITAL*/*LABOR*)	0.002	-0.004	-0.012
	(0.001)	(0.016)	(0.016)
log(*R&D_STOCK*)	-0.000	0.017***	0.019***
	(0.000)	(0.004)	(0.005)
MSCI	0.026***		
	(0.003)		
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
R^2	0.86	0.82	
Number of observations	22,798	22,798	22,798

Table IA.5

Foreign institutional ownership and innovation output: negative binomial regression

This table shows results of negative binomial firm-level panel regressions of innovation output on institutional ownership using a sample of Worldscope nonfinancial and nonutility firms in the 2001–2010 period. The dependent variable is the number of patents applied for with the USPTO (*PATENTS*). In the IV regression, foreign institutional ownership is instrumented with *MSCI* (a dummy variable that equals one if a firm is a member of the MSCI ACWI in a given year, and zero otherwise). Regressions include firm fixed effects using the pre-sample mean scaling method of Blundell, Griffith, and Van Reenen (1999), and the IV estimation is implemented using the control function approach of Blundell and Powell (2004). All explanatory variables are lagged by one year. Variable definitions are provided in Table A.1 in the Appendix. Robust standard errors adjusted for country-year level clustering are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	First stage *IO_FOR* (1)	Negative binomial *PATENTS* (2)	Negative binomial (control function) *PATENTS* (3)
IO_FOR		3.373***	10.511***
		(0.269)	(0.779)
IO_DOM	-0.010***	0.756***	0.945***
	(0.002)	(0.066)	(0.079)
CLOSE	-0.006**	0.540***	0.645***
	(0.003)	(0.064)	(0.063)
FXSALES	0.031***	0.228***	-0.007
	(0.003)	(0.065)	(0.070)
log(*SALES*)	0.005***	0.132***	0.055***
	(0.001)	(0.014)	(0.017)
log(*CAPITAL*/*LABOR*)	0.001***	0.045**	0.035*
	(0.000)	(0.019)	(0.019)
log(*R&D_STOCK*)	0.001***	0.146***	0.134***
	(0.000)	(0.007)	(0.007)
MSCI	0.066***		
	(0.003)		
Year fixed effects	Yes	Yes	Yes
Firm fixed effects (pre-sample)	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
R^2	0.29	0.23	0.23
Number of observations	181,173	181,173	181,173

Table IA.6

Difference-in-differences around stock additions to MSCI ACWI: country-by-year and industry-by-year fixed effects

This table shows results of difference-in-differences regressions of institutional ownership, long-term investment, employment, and innovation output around the time a stock is added to the MSCI ACWI. The sample includes Worldscope nonfinancial and nonutility firms in the 2001–2010 period. Treated firms consist of 574 firms added to the MSCI ACWI during the sample period. Control firms are firms that best match treated firms using propensity scores (nearest neighbor). The dependent variables are foreign institutional ownership (*IO_FOR*), domestic institutional ownership (*IO_DOM*), the sum of capital expenditures and R&D expenditures as a fraction of assets (*CAPEX+R&D*), the logarithm of the number of employees (*LABOR*), and the logarithm of one plus number of patents applied for with the USPTO (*PATENTS*). *TREATED* is a dummy variable that equals one if a firm is added to the MSCI ACWI, and zero otherwise. *AFTER* is a dummy variable that equals one in the year a firm is added to the MSCI ACWI and thereafter, and zero otherwise. Variable definitions are provided in Table A.1 in the Appendix. Robust standard errors adjusted for country-year level clustering are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	*IO_FOR*	*IO_DOM*	*CAPEX+R&D*	*LABOR*	*PATENTS*
	(1)	(2)	(3)	(4)	(5)
TREATED × *AFTER*	0.021***	-0.005	0.006***	0.133***	0.053**
	(0.003)	(0.005)	(0.002)	(0.020)	(0.022)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Country-year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.89	0.97	0.81	0.97	0.95
Number of observations	5,740	5,740	5,740	5,740	5,740

Table IA.7

Difference-in-differences around stock deletions from MSCI ACWI

This table shows results of difference-in-differences regressions of institutional ownership, long-term investment, employment, and innovation output around the time a stock is added to the MSCI ACWI. The sample includes Worldscope nonfinancial and nonutility firms in the 2001–2010 period. Treated firms consist of 167 firms deleted from the MSCI ACWI during the sample period. Control firms are firms that best match treated firms using propensity scores (nearest neighbor). The dependent variables are foreign institutional ownership (*IO_FOR*), domestic institutional ownership (*IO_DOM*), the sum of capital expenditures and R&D expenditures as a fraction of assets (*CAPEX+R&D*), the logarithm of the number of employees (*LABOR*), and the logarithm of one plus number of patents applied for with the USPTO (*PATENTS*). *TREATED* is a dummy variable that equals one if a firm is deleted from the MSCI ACWI, and zero otherwise. *AFTER* is a dummy variable that equals one in the year a firm is deleted from the MSCI ACWI and thereafter, and zero otherwise. Variable definitions are provided in Table A.1 in the Appendix. Robust standard errors adjusted for country-year level clustering are reported in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	*IO_FOR*	*IO_DOM*	*CAPEX+R&D*	*LABOR*	*PATENTS*
	(1)	(2)	(3)	(4)	(5)
TREATED × *AFTER*	-0.019***	-0.011**	-0.002	-0.070*	-0.078**
	(0.005)	(0.005)	(0.004)	(0.040)	(0.038)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.93	0.96	0.77	0.95	0.91
Number of observations	1,670	1,670	1,670	1,670	1,670

Table IA.8

Monitoring channel

This table shows results of ordinary least squares (OLS) firm-level panel regressions of long-term investment, employment, and innovation output on the interaction between foreign institutional ownership and proxies for the monitoring channel using a sample of Worldscope nonfinancial and nonutility firms in the 2001–2010 period. The dependent variables are the sum of capital expenditures and R&D expenditures as a fraction of assets (*CAPEX+R&D*), the logarithm of the number of employees (*LABOR*), and the logarithm of one plus the number of patents applied for with the USPTO (*PATENTS*). *COMMON_LAW* is a dummy variable that equals one when a country has common law legal origin, and zero otherwise. *LOW_GDP* is a dummy variable that equals one when GDP per capita is below the median, and zero otherwise. Regressions include the same control variables as in Tables 3–5 (coefficients not shown). All explanatory variables are lagged by one year. Variable definitions are provided in Table A.1 in the Appendix. Robust standard errors adjusted for country-year level clustering are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	*CAPEX+R&D*		*LABOR*		*PATENTS*	
	(1)	(2)	(3)	(4)	(5)	(6)
IO_FOR	0.069***	0.037***	1.468***	1.214***	0.981***	0.433***
	(0.006)	(0.009)	(0.107)	(0.180)	(0.179)	(0.132)
IO_DOM	-0.002	-0.003	0.747***	0.736***	0.344***	0.331***
	(0.002)	(0.002)	(0.034)	(0.034)	(0.042)	(0.044)
COMMON_LAW × *IO_FOR*	-0.057***		-0.732***		-0.771***	
	(0.009)		(0.193)		(0.242)	
LOW_GDP × *IO_FOR*		0.008		-0.131		0.301
		(0.011)		(0.216)		(0.244)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.21	0.21	0.8	0.8	0.28	0.27
Number of observations	179,125	179,125	164,510	164,510	181,173	181,173

Table IA.9

Foreign institutional ownership and long-term investment: robustness

This table shows results of ordinary least squares (OLS) firm-level panel of long-term investment on institutional ownership using a sample of Worldscope nonfinancial and nonutility firms in the 2001–2010 period. In Columns 1–3, the dependent variable is the sum of capital expenditures and R&D expenditures as a fraction of assets (*CAPEX+R&D*). Column 1 restricts the sample to the 2005–2010 IFRS adoption period. Column 2 restricts the sample to firms with assets in excess of $10 million. In Column 3, the regression includes country-by-year and industry-by-year fixed effects. In Column 4, the dependent variable is the sum of capital expenditures and R&D expenditures as a fraction of sales. Column 5 restricts the sample to firms with positive R&D expenditures. Regressions include the same control variables as those in Table 3 (coefficients not shown). All explanatory variables are lagged by one year. Variable definitions are provided in Table A.1 in the Appendix. Robust standard errors adjusted for country-year level clustering are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
IO_FOR	0.031***	0.018***	0.021***	0.118***	0.016***
	(0.007)	(0.005)	(0.005)	(0.041)	(0.006)
IO_DOM	0.013*	-0.003	0.009**	0.032**	-0.018***
	(0.007)	(0.005)	(0.004)	(0.015)	(0.005)
Year fixed effects	Yes	Yes	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Country-year fixed effects	No	No	Yes	No	No
Industry-year fixed effects	No	No	Yes	No	No
R^2	0.70	0.66	0.65	0.52	0.79
Number of observations	111,184	160,233	175,912	175,912	74,090

Table IA.10

Foreign institutional ownership and innovation output: robustness

This table shows results of ordinary least squares (OLS) firm-level panel of innovation output on institutional ownership using a sample of Worldscope nonfinancial and nonutility firms in the 2001–2010 period. In Columns 1–3, the dependent variable is the logarithm of one plus the number of patents applied with the USPTO (*PATENTS*). Column 1 restricts the sample to the 2001–2008 period. Column 2 restricts the sample to firms with assets in excess of $10 million. In Column 3, the regression includes country-by-year and industry-by-year fixed effects. In Columns 4 and 5, the dependent variables are the patent counts computed over a three-year rolling window and patent counts scaled by technological class and time period, respectively. In Column 6, the dependent variable is the ratio of *PATENTS*-to-*R&D_STOCK*. In Columns 7 and 8, the dependent variables are the logarithm of one plus cite-weighted patent counts and the logarithm of one plus the number of patents applied for simultaneously with the three main patent offices (USPTO, EPO, and JPO), respectively. Regressions include the same control variables as those in Table 5 (coefficients not shown). All explanatory variables are lagged by one year. The sample consists of firms with at least one patent applied for during the sample period. Variable definitions are provided in Table A.1 in the Appendix. Robust standard errors adjusted for country-year level clustering are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IO_FOR	0.399***	0.256**	0.253**	0.156*	0.492***	0.059**	0.275**	0.239**
	(0.112)	(0.105)	(0.097)	(0.085)	(0.132)	(0.029)	(0.132)	(0.111)
IO_DOM	0.097**	0.098***	0.135***	0.056*	0.204***	0.028**	-0.003	0.199***
	(0.039)	(0.037)	(0.022)	(0.033)	(0.049)	(0.011)	(0.041)	(0.066)
Year fixed effects	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-year fixed effects	No	No	Yes	No	No	No	No	No
Industry-year fixed effects	No	No	Yes	No	No	No	No	No
R^2	0.84	0.82	0.83	0.87	0.74	0.54	0.79	0.73
Number of observations	38,643	45,441	48,096	48,096	48,096	38,806	48,096	20,833

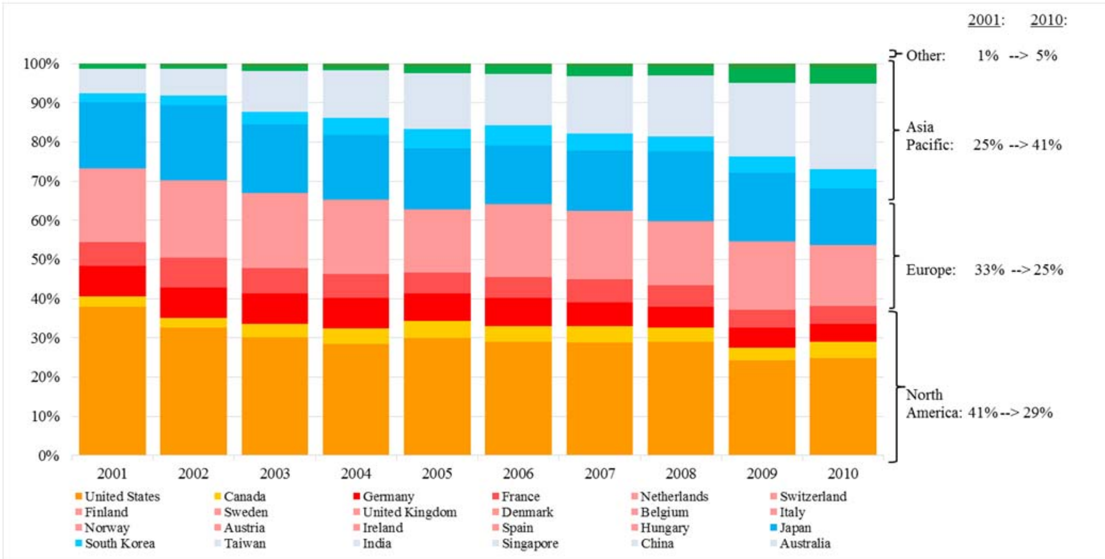
Panel A: Capital expenditures

Panel B: R&D expenditures

Panel C: Patent count

Fig. IA.1. Long-term investment and innovation output by country. This figure shows long-term investment in capital expenditures (CAPEX) in billions of dollars (Panel A), R&D expenditures in billions of dollars (Panel B), and number of patents applied for with the USPTO (Panel C) by firms domiciled in each country. The sample consists of Worldscope nonfinancial and nonutility firms, 2001–2010.

Panel A: Capital expenditures



Panel B: R&D expenditures

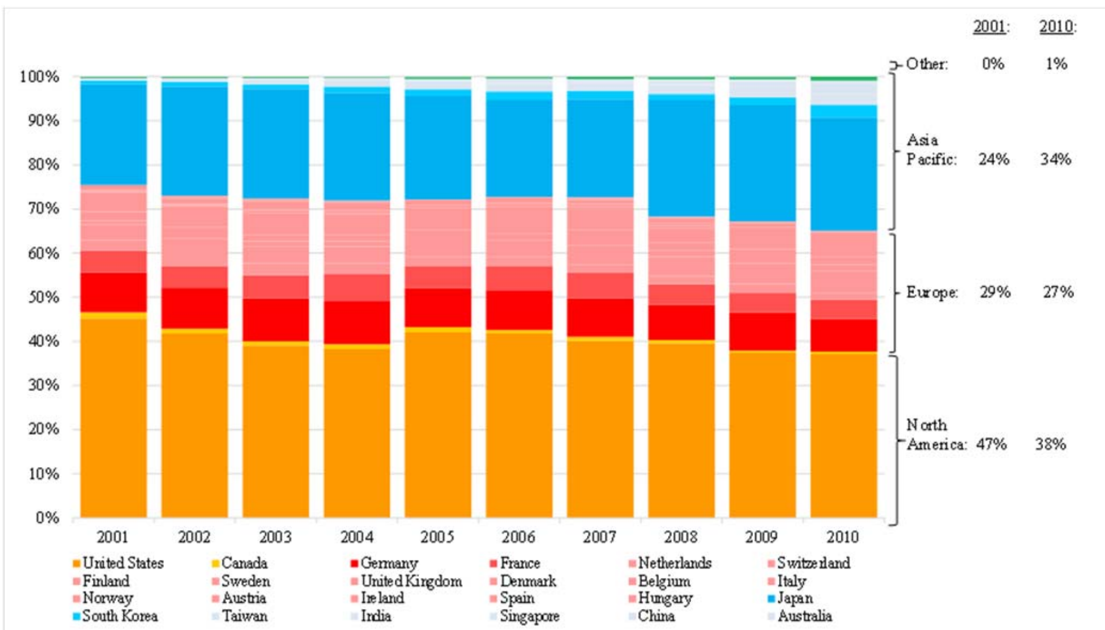


Fig. IA.2 (continued)

Panel C: Patent count

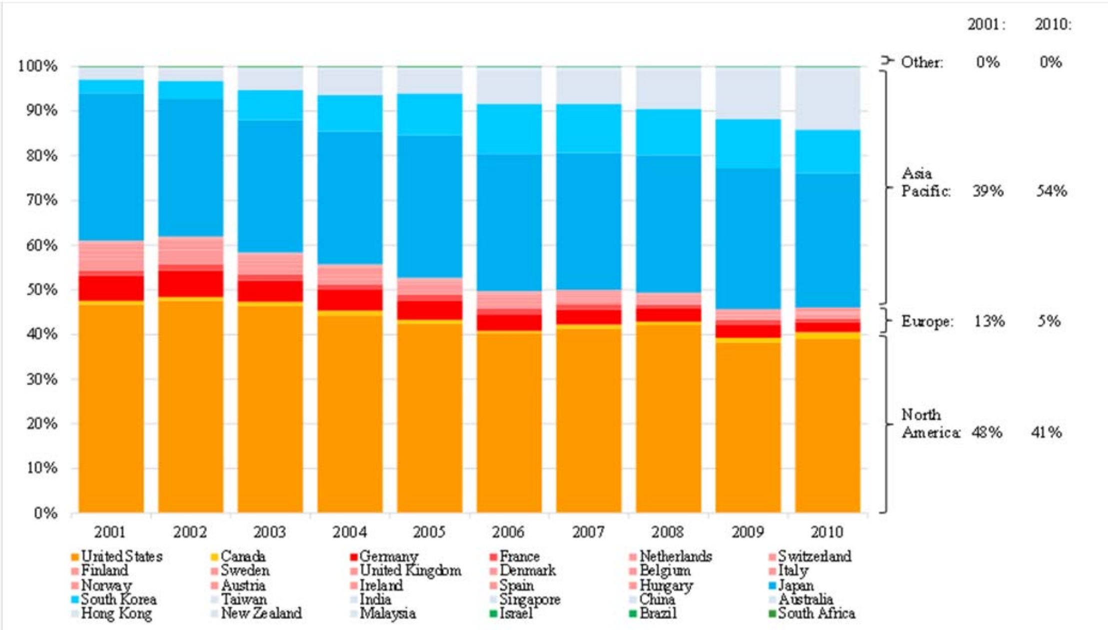
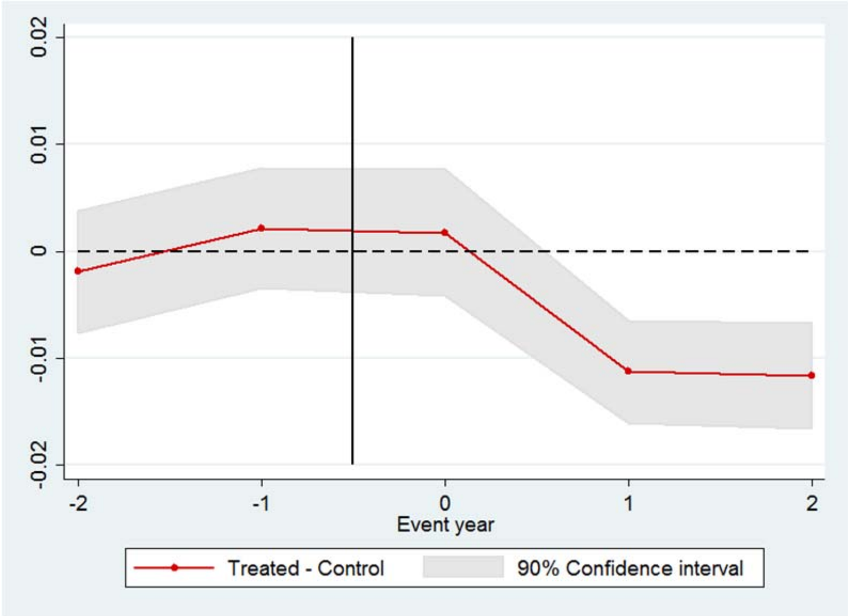


Fig. IA.2. Long-term investment and innovation output by country and year. This figure shows long-term investment in capital expenditures (CAPEX) (Panel A), R&D expenditures (Panel B), and number of patents applied for with the USPTO (Panel C) by firms domiciled in each country as a percentage of the worldwide total. The sample consists of Worldscope nonfinancial and nonutility firms, 2001–2010.

Panel A: Net equity issuance (*NET_EQ_ISSUES*)



Panel B: Net debt issuance (*NET_DEBT_ISSUES*)

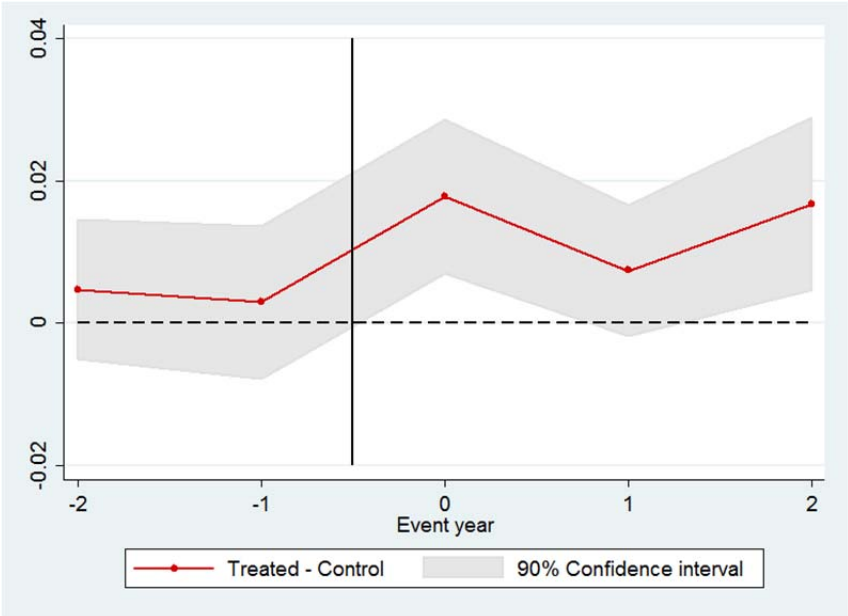


Fig. IA.3. External financing around stock additions to MSCI ACWI. This figure shows point estimates and 90% confidence interval of the differences in net equity issuance (*NET_EQ_ISSUES*) and net debt issuance (*NET_DEBT_ISSUES*) between treated firms and control firms around stock additions to the MSCI ACWI (between year −1 and year 0). Treated firms consist of 574 firms added to the MSCI ACWI during the sample period. Control firms are firms that best match treated firms using propensity scores (nearest neighbor). The sample includes Worldscope nonfinancial and nonutility firms in the 2001–2010 period. Variable definitions are provided in Table A.1 in the Appendix.