Privatization and Innovation: Productivity, New Products, and Patents in China*

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Abstract

We study Chinese firms' innovative activities in the period of privatization. We use Ackerberg, Caves, and Frazer's (forthcoming) method to estimate TFP, which suggests domestic private firms' average TFP converged with that of foreign firms, whereas that of state-owned enterprises lagged behind. We then investigate the relationships between our TFP estimates and other, observed measures of innovation, including the introduction of new products and patent applications. We find: (1) process and product innovations seem complementary to each other, (2) "invention" patents appear more reliable as an indicator of innovations than the other types of Chinese patents, and (3) patenting behaviors are highly heterogeneous across firms of different ownership types.

Keywords: Innovation, Patents, Privatization, Productivity.

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1 Introduction

"China must rely on innovation to achieve continuous and healthy economic development" declared President Xi Jinping,[1] and it is hard to argue against such an obvious statement. In fact, so many world-class technology firms have emerged in China by now, such as Huawei (telecommunications equipment), Lenovo (computers), and Xiaomi (smartphones and internet), that the President's goal seems to have been already achieved. *The Economist* magazine even published a special report arguing that Chinese private-sector firms are embracing innovation and have been responsible for the vast bulk of modern China's economic advance.[2] The report features a story of Sequoia Capital, a prominent venture-capital fund, which invested in Ninebot, a transport-robotics startup, and says that "today it's not just copycats…" Such anecdotal evidence is abundant.

We can also be more skeptical. The Chinese government has long pursued an industrial policy of "indigenous innovation," obliging multinational companies to transfer technology and controlling a large share of assets in "strategic" sectors through state-owned enterprises (SOEs). Unfortunately, the World Bank concludes that the innovation effort at SOEs tend to be unproductive,[3] and *The Economist*'s report quotes "one of the most senior foreign businessmen in China" as saying that SOEs "have the smartest people in science and technology but cannot get a branded product out the door." Central planners have set the national targets for the number of patents (14 per 10,000 people by 2020) and R&D spending (2.8% of GDP, which is America's current rate), and the number of patent applications has soared, but many are deemed worthless.[4] Again, anecdotal evidence is abundant.

Given these pieces of mixed anecdotal evidence, we propose to provide quantitative

[1] Xinhuanet, December 15, 2014.

[2] "Back to business: Special Report on Business in China," September 12, 2015.

[3] World Bank, "China's Growth through Technological Convergence and Innovation" in *China 2030: Building a Modern, Harmonious, and Creative Society*, March 2013.

[4] *The Economist* and WIPO.

evidence on privatization and innovation in China, in its crucial "catch-up" period between 1998 and 2007. We use two main data elements. The first is firm-level data on revenues and other financial-statement items, and other characteristics including ownership types (e.g., SOEs, private firms, and foreign firms). The second is patent-level data on application dates, approval dates, the identity of applicant, and types (i.e., "invention", "design", and "utility" patents). The combined dataset allows us to answer the following questions: (1) who "innovates" in China, in terms of productivity growth, the introduction of new products, and patent applications, and (2) how privatization affects innovation. The answers to these questions would then allow us to derive some normative implications on privatization and innovation.

More specifically, our analysis proceeds in three steps. First, we estimate total factor productivity (TFP) of each firm in each year, from the first data element. We use Ackerberg, Caves, and Frazer's (forthcoming, henceforth ACF) method, which addresses identification problems in Levinsohn and Petrin's (2003, henceforth LP) approach. Second, we analyze the correlation patterns between the TFP estimates (our preferred measure of innovation, arguably with an emphasis on cost-reducing or "process" innovation), the introduction of new products, and the count of patent applications (i.e., two other measures of innovation that are officially reported and directly observed in the first and the second data elements, respectively). Third, we analyze these three measures of innovation by ownership type, and assess how they interacted with privatization (i.e., a change in ownership types). We are currently investigating the process of privatization in detail, to assess the feasibility of dynamic structural analysis.

We have chosen to study these three kinds of innovative activities in such a cautious manner, because data reliability is always an issue when we use official statistics in developing countries in general, and in the Chinese context in particular. From an econometric point of view, we are concerned by the fact that the government has been "encouraging" domestic firms to introduce new products and contribute to the national campaign to achieve patent-count goals. Domestic firms in China have strong incentives to please central planners, and hence the reported "new products" and patent applications may not accurately reflect the underlying innovative activities. Moreover, public- and private-sector firms might respond differently to such encouragements, which further complicates our task of determining who innovates in China.

Our ACF estimation results suggest domestic private firms' average TFP has grown rapidly and converged with that of foreign firms by 2007, our final sample period. By contrast, SOEs' average TFP has also grown but lagged behind those of private and foreign firms by a wide margin. These findings appear consistent with anecdotal evidence pointing to the inefficiency of SOEs. The choice of estimation methods matters, because our alternative estimates generate highly counter-intuitive results. SOEs exhibit a *faster* TFP growth rate than any other types in our OLS estimates, and private firms exhibit *negative* TFP growth in our LP estimates.

Three findings emerge from the analysis of the three measures of innovation (i.e., TFP, new products, and patents). First, our TFP estimates and the introduction of new products (i.e., the fraction of sales from the products that the firm introduced within one year) are positively correlated, which suggests process and product innovations are complementary. This finding is consistent with Athey and Schmutzler's (1995) theoretical prediction. Second, our TFP estimates predict a sizable amount of variation in the count data of "invention" patents but not so much of variation in "design" or "utility" patent counts, which suggests "invention" patents are a more reliable or relevant indicator of innovations than the other types in Chinese patent statistics. This finding is consistent with the fact that applications of "invention" patents have to go through a more rigorous approval process than the others, with the average approval rate below 50%. Third, patenting behaviors are highly heterogeneous across ownership types. Invention patents are most highly correlated with TFP at SOEs, whereas they are most highly correlated with new products at private firms. Semi-foreign firms from Hong Kong, Macau, and Taiwan (HMT) exhibit a pattern similar to SOEs, and other foreign firms appear more similar to domestic private firms, although China may not be their default jurisdiction for patenting. These patenting patterns are new findings for which we have not yet found a lot of counterparts from "anecdotal evidence," but they appear vaguely consistent with the notion that SOEs might employ smartest engineers but do not come up with attractive new products.

Our conclusion is that private firms have been the main driver of innovations in China, with both process and product innovations as complementary activities. Their average TFP has converged with that of foreign firms, which suggests some of them have already finished the catch-up phase of technological development. In comparison, SOEs seem to have lagged behind on average. It would be easy to criticize SOEs for such lackluster performances and declare the victory of entrepreneurship in China, but the fact that the process of privatization has taken place in a gradual and selective manner suggests some selection problem and potential division of labor. This institutional background would motivate us to incorporate the change of ownership types in a more formal analysis, potentially with a dynamic structural approach. We are currently investigating such possibilities, before jumping to a general, normative conclusion.

1.1 Related Literature

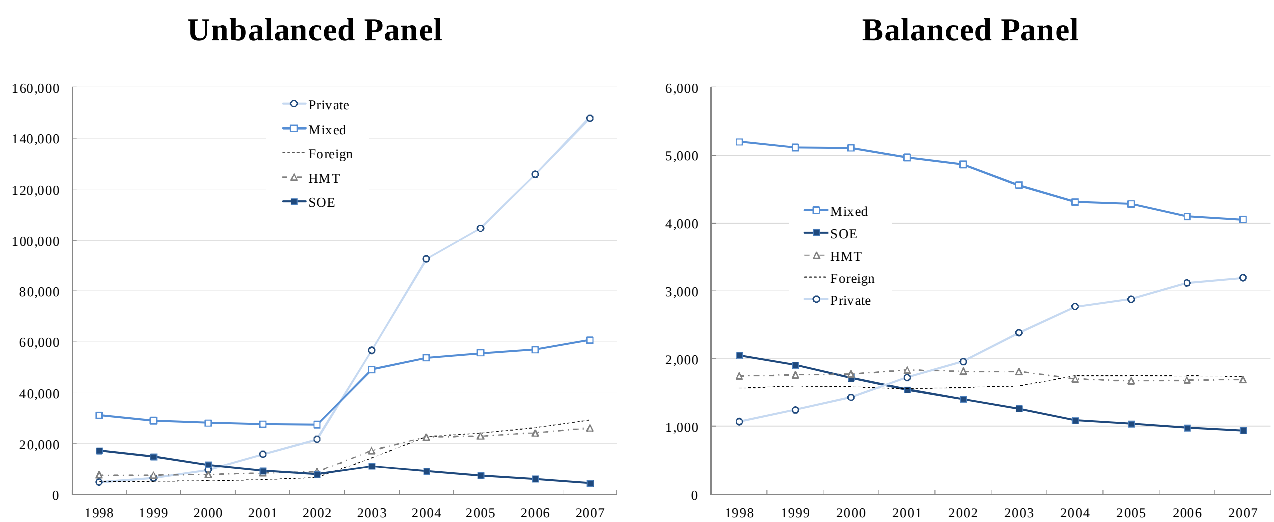
Brandt, Van Biesebroeck, and Zhang (2012, henceforth BVZ), and Yu (2014) estimate TFP of Chinese firms using similar methods.

2 Data

We use two data sources. One is the Survey of Manufacturers between 1998 and 2007. The other is the Chinese patent statistics. In the spirit of Yu (2014), we classify the ownership type of firms into five broad categories based on the official classification: (1) SOEs, (2) mixed ownership including "collective" and other semi-private types, (3) private, (4) HMT, and (5) foreign.[5]

Figure 1 plots the number of firms by ownership type. The left panel concerns the unbalanced panel of firms and incorporates all of the firm-year observations with valid records on deflated inputs and output (as a minimum requirement for OLS estimation of productivity). All ownership types except for SOE experienced increases in firm counts. In particular, the number of private firms exploded, followed by mixed firms. BVZ (2012) study these new entrants' contribution to the aggregate productivity.

Figure 1: Number of Firms by Ownership Type



Note: See main text for definitions.

By contrast, the right panel focuses on the balanced panel. The sheer number of entrants in the unbalanced panel is interesting by itself, but also makes us wonder if we could really pool these entrepreneurial activities with the existing firms without doing injustice to their qualitative difference. Data integrity is another concern, because

[5]We are also currently investigating alternative classification schemes based on ownership share percentages in the spirit of BVZ (2012).

what appears to be entry and exit often turns out to be a basic record-keeping error. For these reasons, we focus on the balanced panel, which drastically reduces the sample size but clarifies the progress of privatization. The numbers of SOE and mixed firms decrease by approximately 1,000 during the sample period, respectively, resulting in an increase of private firms by over 2,000.

Table 1 shows summary statistics for the balanced panel of 11,631 firms between 1998 and 2007. Some variables are not recorded for all of the 116,310 firm-years for the following reasons. First, new-product revenues are not recorded in 2004, which was a census year. Second, capital investment is missing in 1998, the first year of our sample, because we calculate this variable from the change in capital stock between the previous and current years. The logarithm of investment is missing for some more firm-years because our measure of investment is sometimes negative, reflecting occasional drops in capital stock. Third, R&D expenditure is not recorded in early years and contains a lot of zeros, which leads to a much smaller number of observations for the logarithm of R&D.

These two data limitations influence our choice of estimation methods in the subsequent section. Specifically, the applicability of Olley and Pakes's (1996) approach, as well as that of Doraszelski and Jaumandreu (2013), is diminished in the current data context, because the former relies on capital investment and the latter focuses on R&D expenditure.

Table 2 reveals heterogeneity across industries in terms of both the number of firms and its ownership-type composition. Some industries have relatively high numbers of SOEs (e.g., CIC 16, 23, and 36), whereas others feature more HMT and foreign firms (e.g., CIC 18 and 19). The unit of observation is firm-year, and this table focuses on the balanced panel of 11,631 firms. Thus the distribution of ownership types reflects privatizations but not entry/exit.

Table 3 is the transition matrix of firms' ownership types between two adjacent years. Three patterns emerge. First, the transition probabilities along the diagonal

Table 1: Summary Statistics

Variable	Number of observations	Mean	Standard deviation	Minimum	Maximum
Output	116,310	197,488	1,276,397	9	105,000,000
...of which new products	104,673	4.6%	15.8%	0%	100%
Capital	116,310	76,831	627,555	0.35	47,000,000
Labor	116,310	662	2,588	8	166,857
Materials	116,310	146,001	882,127	0.77	53,500,000
Investment	104,679	13,463	212,303	−12,000,000	28,700,000
R&D	60,868	1,697	45,635	−41,431	6,178,631
log output	116,310	10.65	1.42	2.22	18.47
log capital	116,310	9.26	1.73	−1.05	17.67
log labor	116,310	5.56	1.19	2.08	12.02
log materials	116,310	10.36	1.43	−0.26	17.80
log investment	78,037	7.12	2.31	−0.11	17.17
log R&D	15,156	5.87	2.33	−0.14	15.64
Patent applications (all)	116,310	0.43	24.43	0	5,268
Invention (type-1) patents	116,310	0.20	22.60	0	4,940
...of which granted	116,310	0.14	16.46	0	3,474
Design (type-3) patents	116,310	0.11	1.51	0	126
Utility (type-4) patents	116,310	0.12	3.28	0	485

Note: For the balanced panel of 11,631 firms.

Source: Survey of Manufacturers, Patent Statistics.

are high at around 90%, showing that ownership type is stable most of the time. Second, privatizations can take three different paths: (1) 9.71% of SOEs become mixed; (2) 1.17% of SOEs directly transit to private ownership, and (3) 8.08% of mixed firms become private; and (3) HMT and foreign firms occasionally switch types, but rarely become "domestic" firms. Exceptions do exist, such as transitions between domestic and non-domestic types, as well as private, HMT, or foreign firms becoming SOEs, but these patterns occur less than 1% of the times.

These transition patterns are screaming to be studied seriously. One obvious task is to find the determinants of privatization, by using a survival/duration-analysis framework. Another obvious task is to classify ownership types in a finer manner to distinguish between, for example, those who are always SOEs, mixed, or private, and those who were privatized (through the three different paths discussed above). Our current analysis of productivity, new-product, and patent (see subsequent sections)

Table 2: Ownership Types and Industry Composition

Industry	Ownership type					
(2-digit CIC)	SOE	Mixed	Private	HMT	Foreign	Total
13 (Agricultural products)	273	1,014	466	279	510	2,542
14 (Foods)	272	628	267	317	452	1,936
15 (Beverages)	50	240	99	318	409	1,116
16 (Tobacco)	411	173	0	17	3	604
17 (Textile)	986	4,013	2,379	1,349	667	9,394
18 (Apparel & footware)	327	2,604	1,983	3,261	3,045	11,220
19 (Leather & fur)	56	778	568	1,131	783	3,316
20 (Timber)	98	584	498	311	198	1,689
21 (Furniture)	65	381	474	546	405	1,871
22 (Paper)	268	2,003	825	209	187	3,492
23 (Printing)	1,928	1,516	582	832	402	5,260
24 (Cultural articles)	37	428	356	1,266	601	2,688
25 (Petrolum)	135	481	137	71	157	981
26 (Chemical)	1,462	6,316	2,177	1,008	1,370	12,333
27 (Pharmaceutical)	829	2,416	542	447	776	5,010
28 (Chemical fibers)	78	524	176	129	71	978
29 (Rubber)	150	1,319	579	424	399	2,871
30 (Plastics)	260	2,622	1,380	2,136	1,104	7,502
31 (Mineral products)	1,047	3,956	1,497	740	906	8,146
32 (Ferrous metals)	469	1,577	734	197	257	3,234
33 (Non-ferrous metals)	188	657	196	64	89	1,194
34 (Metal products)	112	352	246	145	231	1,086
35 (General machinery)	1,270	4,295	2,103	460	926	9,054
36 (Special machinery)	1,327	2,520	904	251	343	5,345
37 (Transport equipment)	898	1,532	756	321	516	4,023
39 (Electrical machinery)	166	1,116	915	278	412	2,887
40 (Electronics)	400	1,684	622	542	635	3,883
41 (Precision instruments)	287	547	222	357	448	1,861
42 (Artwork)	119	275	95	111	194	794
Total	13,968	46,551	21,778	17,517	16,496	116,310

Note: The unit of observation is firm-year.

can and should be repeated with this finer typology that reflects the dynamics of privatizations.

Table 3: Transition Matrix of Ownership Types (%)

Current (t) ownership type	Ownership type next year ($t+1$) SOE	Mixed	Private	HMT	Foreign	Total
SOE	88.74	9.71	1.17	0.19	0.19	100.00
Mixed	0.76	90.32	8.08	0.40	0.43	100.00
Private	0.06	7.82	91.24	0.42	0.46	100.00
HMT	0.06	0.84	0.58	94.40	4.11	100.00
Foreign	0.10	0.82	0.47	3.80	94.81	100.00
Total	11.38	39.51	19.78	15.06	14.26	100.00

Note: The balanced panel of 11,631 firms.

3 Estimating Productivity

3.1 Production Function Estimation

As a preliminary analysis, Table 4 compares the results of production function estimation by three different approaches: (1) OLS, (2) GMM by Levinsohn-Petrin method, and (3) GMM by Ackerberg-Caves-Frazer method. These regressions pool the data across all industries and ignore their technological differences. Nevertheless, the results are instructive as an overview of these data patterns. First, the OLS estimates of the capital coefficient, β_k, are larger than those from the two GMM approaches, presumably because of the simultaneity bias that the latter methods aim to address. That is, more productive firms have greater incentives to invest in capital stock than less productive firms, but the resulting higher outputs would be wrongly interpreted as the contribution of increased capital stock in OLS regressions. Second, both OLS and ACF estimates indicate a clear and intuitive productivity ranking among the five ownership types, with SOEs at the bottom and foreign firms at the top: $\omega^{soe} < \omega^{mix} < \omega^{pri} < \omega^{hmt} < \omega^{for}$. The LP estimates appear silent on this aspect. Third, both OLS and ACF estimates suggest an upward time trend in productivity, although the LP estimates lack a clear pattern. In a rapidly modernizing economy like China's, such patterns of productivity growth appear natural.

Tables 5 (OLS), 6 (LP), and 7 (ACF) are more serious versions of Table 4. Be-

Table 4: Production Function Estimates (All Industries)

Dependent variable: Output (y_{it})	(1) OLS	(2) GMM (LP)	(3) GMM (ACF)	(4) OLS	(5) GMM (LP)	(6) GMM (ACF)
Capital (k_{it})	.0591	.0350	.0373	.0483	.0057	.0228
	(.0010)	(.0019)	(.0016)	(.0010)		
Labor (l_{it})	.0537	.0492	.0399	.0871	.0753	.1059
	(.0013)	(.0013)	(.0021)	(.0014)		
Materials (m_{it})	.8758	.9195	.9232	.8567	.9484	.8817
	(.0011)	(.0052)	(.0056)	(.0012)		
Ownership type:						
Mixed	–	–	–	.0589	.0046	.1477
				(.0034)		
Private	–	–	–	.0645	−.0044	.1624
				(.0040)		
HMT	–	–	–	.1090	.0034	.2341
				(.0041)		
Foreign	–	–	–	.1563	−.0058	.2869
				(.0042)		
Year:						
1999	–	–	–	.0419	–	–
				(.0044)		
2000	–	–	–	.0844	−.0141	−.3011
				(.0044)		
2001	–	–	–	.0828	−.0253	−.2712
				(.0044)		
2002	–	–	–	.1003	−.0323	−.2803
				(.0044)		
2003	–	–	–	.1655	−.0399	−.2692
				(.0044)		
2004	–	–	–	.2187	−.0336	−.2107
				(.0044)		
2005	–	–	–	.2723	−.0307	−.1596
				(.0044)		
2006	–	–	–	.3157	−.0332	−.1073
				(.0044)		
2007	–	–	–	.3452	−.0306	−.0639
				(.0045)		
Constant	.7316	.5423	.5331	.5963	.4353	.7350
	(.0077)	(.0435)	(.0438)	(.0108)		
Industry dummies	*No*	*No*	*No*	*Yes*	*Yes*	*Yes*
Num. observations	116,310	104,679	104,679	116,310	104,679	104,679
Adjusted R^2	.9360			.9455		

Note: Omitted categories are SOE (ownership type) and 1998 (year). Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

cause production technologies and institutional contexts differ across industries, we prefer productivity estimates from regressions by industry. Let us start from the OLS estimates in Table 5. First, these regressions show an obvious fact that industries differ from each other in terms of basic features such as β_k and β_l. Second, the fourth column indicates constant returns to scale, which is the literature's usual assumption. Third, the last column suggests the Chinese economy is moderately labor-intensive on average, but $\beta_k > \beta_l$ in those industries that we typically associate with capital-intensive production processes, such as tobacco (CIC 16), chemical (26), pharmaceutical (27), and several electric and electronic industries (30s and 40s).

Table 5: Production Function Estimates by Industry (OLS)

Industry (2-digit CIC)	Coefficient estimates: Capital (β_k)	Labor (β_l)	Materials (β_m)	Returns to scale ($\beta_k + \beta_l + \beta_m$)	Capital/labor intensity (β_k / β_l)
13 (Agricultural products)	.0551	.0865	.8945	1.0361	0.6370
14 (Foods)	.0361	.0480	.9191	1.0032	0.7521
15 (Beverages)	.0034	.0591	.9656	1.0281	0.0575
16 (Tobacco)	.2091	.0727	.8342	1.1160	2.8762
17 (Textile)	.0211	.0275	.9540	1.0026	0.7673
18 (Apparel & footware)	.0612	.1439	.7862	0.9913	0.4253
19 (Leather & fur)	.0448	.1533	.8075	1.0056	0.2922
20 (Timber)	.0491	.1118	.8342	0.9951	0.4392
21 (Furniture)	.0394	.0833	.9008	1.0235	0.4730
22 (Paper)	.0108	.0038	.9838	0.9984	2.8421
23 (Printing)	.0901	.0622	.8488	1.0011	1.4486
24 (Cultural articles)	.0461	.1263	.8214	0.9938	0.3650
25 (Petrolum)	.0475	.0560	.8715	0.9750	0.8482
26 (Chemical)	.0600	.0254	.8886	0.9740	2.3622
27 (Pharmaceutical)	.0774	.0386	.9124	1.0284	2.0052
28 (Chemical fibers)	.0217	.0414	.9369	1.0000	0.5242
29 (Rubber)	.0991	.1139	.7343	0.9473	0.8701
30 (Plastics)	.0497	.0684	.8826	1.0007	0.7266
31 (Mineral products)	.0518	.0426	.8716	0.9660	1.2160
32 (Ferrous metals)	.0195	.0598	.9359	1.0152	0.3261
33 (Non-ferrous metals)	.0618	.0607	.8661	0.9886	1.0181
34 (Metal products)	.0907	.0116	.8862	0.9885	7.8190
35 (General machinery)	.0486	.0181	.9327	0.9994	2.6851
36 (Special machinery)	.0369	.0192	.9412	0.9973	1.9219
37 (Transport equipment)	.0201	.0328	.9495	1.0024	0.6128
39 (Electrical machinery)	.0400	.0521	.9070	0.9991	0.7678
40 (Electronics)	.0618	.0561	.9024	1.0203	1.1016
41 (Precision instruments)	.0918	.0559	.8101	0.9578	1.6422
42 (Artwork)	.0630	.0593	.8636	0.9859	1.0624
Average	.0554	.0617	.8842	1.0014	0.8980

Note: Balanced panel.

Table 6 shows the industry-by-industry estimates from the LP approach. Although some qualitative patterns look similar to the OLS results, the returns to scale is less than one (i.e., decreasing returns to scale) on average, and the capital coefficient is slightly greater than the labor coefficient on average, which are somewhat surprising.

Table 6: Production Function Estimates by Industry (Levinsohn-Petrin GMM)

Industry (2-digit CIC)	Coefficient estimates: Capital (β_k)	Labor (β_l)	Materials (β_m)	Returns to scale ($\beta_k + \beta_l + \beta_m$)	Capital/labor intensity (β_k/β_l)
13 (Agricultural products)	.0514	.0817	.9253	1.0584	0.6291
14 (Foods)	.0967	.0342	.6922	0.8231	2.8275
15 (Beverages)	.0611	.0405	.8769	0.9785	1.5086
16 (Tobacco)	.1721	.0942	.6946	0.9609	1.8270
17 (Textile)	.0480	.0253	.8460	0.9193	1.8972
18 (Apparel & footware)	.0405	.1215	.8468	1.0088	0.3333
19 (Leather & fur)	.0207	.1241	.8722	1.0170	0.1668
20 (Timber)	.0264	.0569	.9163	0.9996	0.4640
21 (Furniture)	.0668	.0852	.7732	0.9252	0.7840
22 (Paper)	.0611	.0011	.8988	0.9610	55.5455
23 (Printing)	.0588	.0622	.9011	1.0221	0.9453
24 (Cultural articles)	.0274	.1115	.8701	1.0090	0.2457
25 (Petrolum)	.0390	.0501	.8875	0.9766	0.7784
26 (Chemical)	.0329	.0204	.9387	0.9920	1.6127
27 (Pharmaceutical)	.1326	.0369	.6160	0.7855	3.5935
28 (Chemical fibers)	.0609	.0378	.8707	0.9694	1.6111
29 (Rubber)	.0489	.0371	.8940	0.9800	1.3181
30 (Plastics)	.0315	.0620	.9231	1.0166	0.5081
31 (Mineral products)	.0304	.0264	.9287	0.9855	1.1515
32 (Ferrous metals)	.0039	.0563	.9612	1.0214	0.0693
33 (Non-ferrous metals)	.0386	.0365	.9255	1.0006	1.0575
34 (Metal products)	.0530	.0092	.9534	1.0156	5.7609
35 (General machinery)	.0641	.0135	.7498	0.8274	4.7481
36 (Special machinery)	.0508	.0178	.8453	0.9139	2.8539
37 (Transport equipment)	.0285	.0327	.8335	0.8947	0.8716
39 (Electrical machinery)	.0484	.0480	.7711	0.8675	1.0083
40 (Electronics)	.0059	.0501	1.0028	1.0588	0.1178
41 (Precision instruments)	.0295	.0459	.9083	0.9837	0.6427
42 (Artwork)	.0508	.0329	.9097	0.9934	1.5441
Average	.0511	.0501	.8632	0.9643	1.0198

Note: Balanced panel.

Table 7 shows the industry-by-industry estimates based on the ACF method. In six out of 29 industries (CIC 13, 22, 34, 37, 40, and 41), either β_k or β_l is slightly negative and statistically indistinguishable from zero, which suggests strong adjustments for the simultaneity bias in this estimation approach. The returns to scale estimate is close to unity and similar to the OLS result. Most importantly, the average capital/labor intensity is approximately a half of the OLS and LP results. In other words, the ACF estimates say the "world's factory" is significantly labor-intensive overall, which conforms to the conventional view on the Chinese manufacturing sector during the sample period.

Table 7: Production Function Estimates by Industry (Ackerberg-Caves-Frazer GMM)

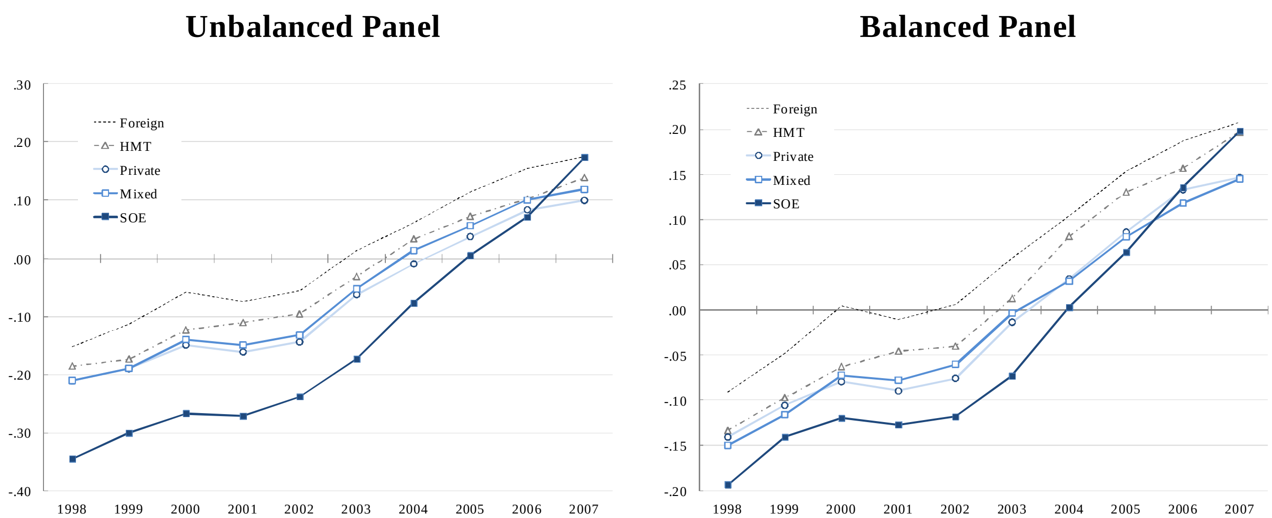
Industry	Coefficient estimates			Returns to	Capital/labor
(2-digit CIC)	Capital	Labor	Materials	scale	intensity
	(β_k)	(β_l)	(β_m)	($\beta_k + \beta_l + \beta_m$)	(β_k/β_l)
13 (Agricultural products)	-.0525	.7313	.3094	0.9882	-
14 (Foods)	-.0077	.3691	.7366	1.0980	-
15 (Beverages)	.0059	.0337	.8356	0.8752	0.1751
16 (Tobacco)	.1599	.0193	.6710	0.8502	8.2850
17 (Textile)	.0007	.1576	.8820	1.0403	0.0044
18 (Apparel & footware)	.0396	.1217	.8492	1.0105	0.3254
19 (Leather & fur)	.0228	.0979	.8971	1.0178	0.2329
20 (Timber)	.0263	.0757	.9042	1.0062	0.3474
21 (Furniture)	.0642	.0292	.7917	0.8851	2.1986
22 (Paper)	.0379	-.0311	.7591	0.7659	-
23 (Printing)	.0627	.0572	.8993	1.0192	1.0962
24 (Cultural articles)	.0268	.1158	.8686	1.0112	0.2314
25 (Petrolum)	.0298	.0381	.9085	0.9764	0.7822
26 (Chemical)	.0347	.0138	.9419	0.9904	2.5145
27 (Pharmaceutical)	.0536	.0263	.9598	1.0397	2.0380
28 (Chemical fibers)	.0770	.2374	.6948	1.0092	0.3243
29 (Rubber)	.0501	.0884	.8476	0.9861	0.5667
30 (Plastics)	.0325	.0582	.9239	1.0146	0.5584
31 (Mineral products)	.0309	.0243	.9294	0.9846	1.2716
32 (Ferrous metals)	.0014	.0312	.9854	1.0180	0.0449
33 (Non-ferrous metals)	.0304	.0545	.9211	1.0060	0.5578
34 (Metal products)	.0585	-.0027	.9582	1.0140	-
35 (General machinery)	.0141	.0814	.9455	1.0410	0.1732
36 (Special machinery)	.0065	.3812	.7219	1.1096	0.0171
37 (Transport equipment)	-.0094	.2772	.8451	1.1129	-
39 (Electrical machinery)	.0475	.1146	.7322	0.8943	0.4145
40 (Electronics)	-.0021	.4011	.6963	1.0953	-
41 (Precision instruments)	.0421	-.0077	.9277	0.9621	-
42 (Artwork)	.0448	.0326	.9219	0.9993	1.3742
Average	.0392	.0859	.8651	0.9902	0.4562

Note: Balanced panel.

3.2 Productivity by Ownership Type

In this subsection, we plot the trajectories of TFP estimates by ownership type, based on the production function estimates in the previous section (i.e., Tables 5, 6, and 7). Our purpose is to obtain a "big picture" of productivity dynamics, but we should keep in mind that firm-level heterogeneity washes away most of these categorical patterns at the ownership type level. That is, large standard deviations surround these categorical means.

Figure 2: TFP Estimate by Ownership Type (OLS)



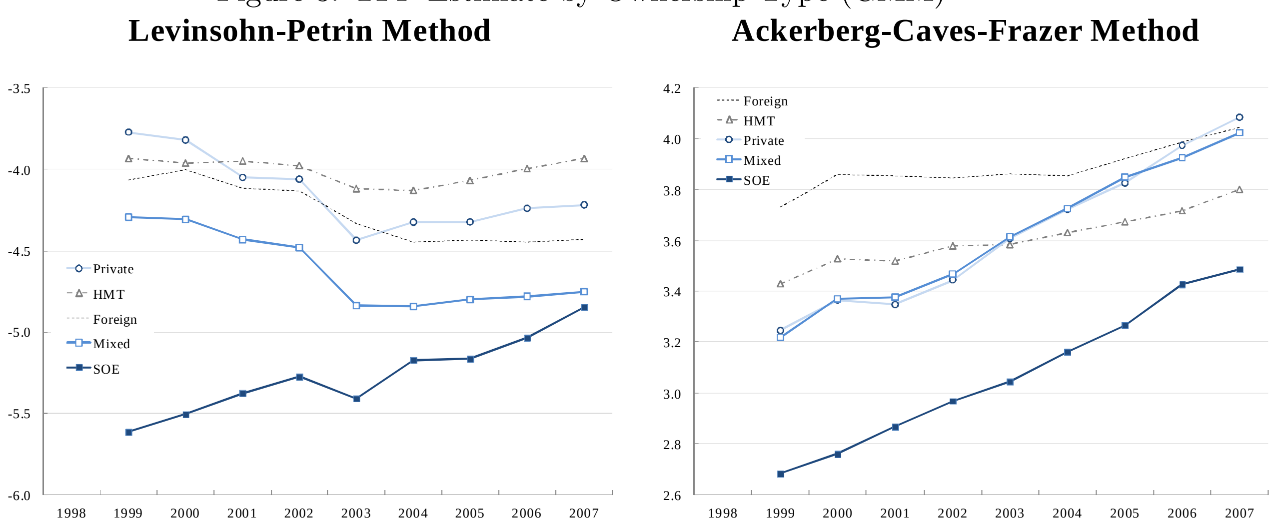
Note: Note here.

Figure 2 compares the two sets of OLS estimates, which are based on the unbalanced-panel and the balanced-panel versions of the dataset, respectively. In Figure 1, we have already found that the "entry" of new firms, primarily in the private sector, dominates all other actions in the unbalanced panel, and that the balanced panel is only a small fraction of this larger dataset. We have chosen to focus on the balanced panel in order to isolate the contributions of entry and exit (of qualitatively different firms) to the productivity dynamics.

These considerations notwithstanding, the plots of the unbalanced and balanced panels in Figure 2 appear surprisingly similar, sharing all of the three major patterns in common. First, an upward time trend is evident, as foreshadowed by the preliminary regressions in Table 4. Second, the overall ranking of the five types is also clear, with foreign and HMT firms consistently outperforming the domestic types, and with SOEs at the bottom most of the time.

However, the third and the most surprising feature is that SOEs' productivity growth appears to accelerate suddenly in 2004, surpass the other domestic types, and almost completely converge to foreign firms' performance by 2007. Taken at face value, this finding would suggest most China watchers had been wrong in associating SOEs with inefficiency, but our subsequent analysis proves this picture to be an illusion.

Figure 3: TFP Estimate by Ownership Type (GMM)



Note: Note here.

Figure 3 shows the two sets of GMM estimates, both of which put SOEs' average productivity level strictly below those of all other types, thereby revealing that the "SOEs' catch-up" in Figure 2 was too good to be true. We are curious why such a dramatic pattern emerged in the OLS results but not in the GMM results, and suspect the simultaneity bias is particularly severe when the dataset contains inefficient and politically oriented entities (i.e., not our usual profit-maximizers).

A few important differences stand out from the comparison of the left (LP) and the right (ACF) panels in Figure 3. The overall productivity rankings are similar between LP and ACF, but the LP result puts domestic private firms at or near the top in most years (i.e., frequently outperforming HMT and foreign firms), which is a little difficult to interpret. Another strange feature is the lack of positive time trend in LP during the first five year, with an exception of SOEs.

By contrast, the ACF results appear straightforward and more intuitive. First, SOEs' productivity improves rapidly, but never surpasses that of HMT or foreign firms. Second, mixed and private firms do catch up with HMT and foreign firms, and their productivity growth seems to accelerate around 2001, 2002, and 2003, potentially in relation to the WTO accession of China. Third, besides these patterns of productivity convergence between domestic and non-domestic firms, the overall time trend and ranking appear in line with the preliminary, pooled regressions in Table 4.

4 New Products and Patent Applications

Now that we have obtained our TFP benchmark, we can analyze other, more direct measures of innovative activities in relation to the TFP estimates.

4.1 Fraction of Revenue from "New Products"

Do process innovation and product innovation tend to occur at the same firms and/or in the same years? In other words, are these two types of innovations complements or substitutes?

Table 8 investigates the correlation patterns between productivity and new products, by showing regressions of the fraction of revenue from new products (%) on our ACF estimates of productivity level and growth, as well as their interactions with ownership types.

Table 8: Productivity (ACF) and Revenue from "New Products"

Dependent variable: Fraction of revenue from "new products"	(1)	(2)	(3)	(4)	(5)	(6)
Productivity ($\hat{\omega}_{it}$) $\times$ SOE	$.0165^{***}$	$.0147^{***}$	$.0149^{***}$	$.0184^{***}$	$.0167^{***}$	$.0180^{***}$
	(.0011)	(.0011)	(.0011)	(.0012)	(.0012)	(.0012)
Productivity ($\hat{\omega}_{it}$) $\times$ Mixed	$.0174^{***}$	$.0155^{***}$	$.0191^{***}$	$.0187^{***}$	$.0168^{***}$	$.0219^{***}$
	(.0008)	(.0008)	(.0008)	(.0008)	(.0009)	(.0008)
Productivity ($\hat{\omega}_{it}$) $\times$ Private	$.0138^{***}$	$.0118^{***}$	$.0165^{***}$	$.0150^{***}$	$.0130^{***}$	$.0193^{***}$
	(.0009)	(.0010)	(.0009)	(.0010)	(.0010)	(.0010)
Productivity ($\hat{\omega}_{it}$) $\times$ HMT	$.0134^{***}$	$.0121^{***}$	$.0182^{***}$	$.0145^{***}$	$.0132^{***}$	$.0205^{***}$
	(.0011)	(.0011)	(.0011)	(.0012)	(.0012)	(.0012)
Productivity ($\hat{\omega}_{it}$) $\times$ Foreign	$.0117^{***}$	$.0104^{***}$	$.0148^{***}$	$.0130^{***}$	$.0117^{***}$	$.0175^{***}$
	(.0009)	(.0009)	(.0009)	(.0010)	(.0010)	(.0010)
Productivity growth ($\Delta\hat{\omega}_{it}$) $\times$ SOE	–	–	–	$.0125^{***}$	$.0116^{***}$	.0014
	–	–	–	(.0031)	(.0031)	(.0031)
Productivity growth ($\Delta\hat{\omega}_{it}$) $\times$ Mixed	–	–	–	$.0155^{***}$	$.0145^{***}$	$.0035^{**}$
	–	–	–	(.0017)	(.0017)	(.0017)
Productivity growth ($\Delta\hat{\omega}_{it}$) $\times$ Private	–	–	–	$.0087^{***}$	$.0074^{***}$	$-.0023$
	–	–	–	(.0023)	(.0023)	(.0022)
Productivity growth ($\Delta\hat{\omega}_{it}$) $\times$ HMT	–	–	–	$.0136^{***}$	$.0128^{***}$	$.0055^{**}$
	–	–	–	(.0028)	(.0028)	(.0028)
Productivity growth ($\Delta\hat{\omega}_{it}$) $\times$ Foreign	–	–	–	$.0090^{***}$	$.0080^{***}$	$-.0019$
	–	–	–	(.0028)	(.0028)	(.0027)
Mixed	$-.0168^{***}$	$-.0163^{***}$	$-.0158^{***}$	$-.0122^{***}$	$-.0116^{***}$	$-.0135^{***}$
	(.0039)	(.0039)	(.0038)	(.0043)	(.0043)	(.0042)
Private	$-.0242^{***}$	$-.0249^{***}$	$-.0168^{***}$	$-.0200^{***}$	$-.0206^{***}$	$-.0143^{***}$
	(.0035)	(.0045)	(.0045)	(.0050)	(.0050)	(.0049)
HMT	$-.0164^{***}$	$-.0179^{***}$	$-.0276^{***}$	$-.0127^{**}$	$-.0142^{**}$	$-.0253^{***}$
	(.0050)	(.0050)	(.0049)	(.0055)	(.0055)	(.0055)
Foreign	$-.0048$	$-.0063$	$-.0105^{**}$	$-.0028$	$-.0044$	$-.0113^{**}$
	(.0048)	(.0048)	(.0047)	(.0053)	(.0053)	(.0052)
Size (fitted value of output, $\hat{y}_{it}$)	–	–	$.0263^{***}$	–	–	$.0264^{***}$
	–	–	(.0004)	–	–	(.0005)
Constant	$.0552^{***}$	$.0462^{***}$	$-.2867^{***}$	$.0539^{***}$	$.0442^{***}$	$-.2796^{***}$
	(.0051)	(.0053)	(.0077)	(.0055)	(.0057)	(.0081)
Year dummies	*No*	*Yes*	*Yes*	*No*	*Yes*	*Yes*
Industry dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Num. of observations	93,044	93,044	93,044	81,413	81,413	81,413
Adjusted R^2	.0579	.0591	.0930	.0595	.0606	.0946

Note: Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Columns 4, 5, and 6 use the lagged productivity levels and the lagged predicted outputs.

Several patterns emerge. First, the introduction of new products is positively correlated with both productivity level and its growth rate in most specifications, which suggests complementarity between process and product innovations.

Second, mixed-ownership firms exhibit consistently higher coefficient estimates on $\hat{\omega}_{it}$ than most other types. As we will see later, mixed firms' patent application activities are also closely related to the new-product introduction, so we might believe there is something good and real about mixed firms' new products.

Third, the ownership-type dummies suggest SOEs tend to report more new-product revenues than the other types. By contrast, private firms and HMT firms tend to report the least.

Fourth, the coefficient on firm size (measured by the fitted values of output) is positive, suggesting that the bigger firms' revenues tend to rely more on new products.

Finally, a comparison of the adjusted R^2 between the first and the last three columns indicate the productivity growth terms improve the fit only negligibly.

Two caveats are in order. First, "new product" definition is at the firm-year level and not always clear or uniform throughout the sample. Second, new products' revenues are part of y_{it}, and hence are potentially correlated with productivity estimates in a rather automatic manner. We can think of two possibilities. If these new products represent higher-quality goods and start commanding higher prices than the existing goods from the initial year of introduction, then our TFP estimates (ω_{it}) incorporates such revenue-contribution, leading to a mechanically positive correlation. If new products take more than a year to achieve measurable extra contribution to the firms' revenues, then we need not worry about spurious correlations.

4.2 Patenting Behavior

A priori, we have no reason to believe patents (especially in China) reflect any underlying innovative activities, because the intellectual property regime is a relatively new development and has yet to be established completely. Thus, as a basic viewpoint, we share Igami and Subramanyam's (2015) conservative attitude toward patenting activities, and refrain from naively assuming that patents necessarily reflect innovations.

Instead, we put more weights on our independently estimated TFP measures (and "new product" records, to some extent), taking these variables as relatively more structural and fundamental objects that firms and governments would have harder time manipulating. We would then ask whether and how firms' patenting activities actually correlate with these arguably more "objective" measures of process (and product) innovation.

Table 9 shows the regressions of patent application counts on TFP estimates and new-product records, as well as their interactions with ownership types. Because patent applications are count data, we use negative binomial regression, which nests Poisson regression as a special case. Each of the five columns regresses the application count of a different type of patents: (1) all types pooled together, (2) type-4 "utility" patents, (3) type-3 "design" patents, and (4) type-1 "invention" patents. The fifth column also uses type-1 patents, but focuses on those type-1 patent applications that are eventually approved and granted by the authority. This type of patents is perceived to represent the most "serious" claims of inventions and undergoes the examination (the approval rate is less than about 50%), whereas the other two types of patents do not seem to go through rigorous examination processes.

This table contains a lot of information, so let us examine the results carefully. First, patents are positively correlated with both TFP and new products, but firm size is the strongest determinant of patent applications in the sense that its coefficients are by far the most precisely estimated. Comparisons of the specifications with and without firm size on RHS (unreported) reveal that firm size contributes the most to the pseudo R^2 among all regressors. This is a familiar phenomenon in the literature. Igami and Subramanyam (2015) find a similar pattern in the US patent statistics, even after controlling for other, more direct measures of innovation. See Cohen (2010) for a survey on the related literature about firm size and R&D.

Second, different types of patents show different patterns. The coefficient estimates exhibit a variety of patterns between columns 2, 3, and 4, but probably the

Table 9: Productivity (ACF), "New Products", and Patents (Negative Binomial Regression)

Dependent variable: Patent application count	(1) All types	(2) Type 4 (utility)	(3) Type 3 (design)	(4) Type 1 (invention)	(5) Type 1 granted
Productivity ($\hat{\omega}_{it}$) × SOE	.6045***	.4018***	.6485***	.9350***	.9082***
	(.0484)	(.0907)	(.0552)	(.0755)	(.0875)
Productivity ($\hat{\omega}_{it}$) × Mixed	.6408***	.6173***	.5911***	.7059***	.7067***
	(.0356)	(.0644)	(.0403)	(.0461)	(.0537)
Productivity ($\hat{\omega}_{it}$) × Private	.5801***	.5482***	.4773***	.7283***	.7647***
	(.0435)	(.0719)	(.0545)	(.0662)	(.0823)
Productivity ($\hat{\omega}_{it}$) × HMT	.7064***	.6836***	.5886***	.8074***	.7759***
	(.0483)	(.0821)	(.0578)	(.0699)	(.0805)
Productivity ($\hat{\omega}_{it}$) × Foreign	.6256***	.655***	.4595***	.6349***	.6264***
	(.0443)	(.0767)	(.0520)	(.0568)	(.0651)
New product revenue (%)× SOE	1.2501***	1.2565*	1.1374***	1.6184***	1.5665***
	(.3599)	(.7229)	(.3238)	(.3635)	(.4217)
New product revenue (%)× Mixed	1.7207***	1.2474***	1.9155***	1.8479***	2.0262***
	(.1899)	(.3383)	(.1741)	(.1852)	(.2041)
New product revenue (%)× Private	1.0273***	1.0247*	1.3899***	1.7547***	1.9262***
	(.2972)	(.5257)	(.3191)	(.3349)	(.3976)
New product revenue (%)× HMT	.1170	−.0059	.4466	1.4642***	1.0521**
	(.3350)	(.6135)	(.3428)	(.3655)	(.4384)
New product revenue (%)× Foreign	1.1781***	.6152	1.0219***	1.8045***	1.6256***
	(.2909)	(.5088)	(.2929)	(.2673)	(.3040)
Mixed	.1168	−.2110	.3636*	1.0546***	.9474***
	(.1763)	(.3252)	(.2018)	(.3162)	(.3587)
Private	.5327**	.5161	.6159**	.7477*	.3975
	(.2115)	(.3694)	(.2492)	(.3872)	(.4666)
HMT	.1728	.0640	.5570**	.6736*	.5904
	(.2265)	(.3941)	(.2744)	(.3976)	(.4548)
Foreign	.0157	−.3747	.8257***	1.0377***	.8574**
	(.2234)	(.3907)	(.2678)	(.3713)	(.4209)
Size (fitted value of output, $\hat{y}_{it}$)	.8603***	.8100***	.9526***	1.0056***	1.0090***
	(.0191)	(.0371)	(.0215)	(.0225)	(.0258)
Constant	−14.182***	−13.485***	−18.248***	−19.404***	−19.581***
	(.3660)	(.6577)	(.5248)	(.5648)	(.6423)
Year dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
α	26.0108	86.4475	15.5566	14.0580	13.8182
	(.5380)	(2.7621)	(.4835)	(.5832)	(.7445)
Log likelihood	−26,858	−12,079	−14,837	−9,431	−6,410
Num. of observations	93,044	93,044	93,044	93,044	93,044
Psuedo R^2	.1048	.0649	.1676	.2499	.2723

Note: Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Columns 4, 5, and 6 use the lagged productivity levels and the lagged predicted outputs.

most important feature is their differences in terms of fit. Our RHS variables explain a fair amount of variation in type-1 "invention" patent applications (pseudo R^2 is .2499) and those type-1 applications that are eventually approved (.2723), whereas they have a harder time predicting type-3 "design" patents (.1676) and hardly explain any variation in type-4 "utility" patents (.0649). Thus the count of granted type-1 patents is the most useful indicator of innovation in the sense that it co-varies meaningfully with what most economists would deem more fundamental.

Third, different types of firms patent differently. Type-1 patenting activity seems more "related" or "responsive" to TFP at SOEs, and to new products at mixed and private firms, than at the other types of firms. One possible interpretation of this heterogeneity is that mixed and private firms are more focused on product innovation, whereas SOEs with high productivity (or "profitability", because we rely on revenue-based TFP estimates) can afford large expenditures on patenting activities.

HMT and foreign firms exhibit curious patterns as well. Type-1 patents at HMT firms are almost as closely related to TFP as at SOEs, but their relation to new products is the weakest of all ownership types. By contrast, foreign firms' type-1 patents seem the least related to TFP but moderately related to new products. Yet another interesting feature of HMT and foreign firms in columns 4 and 5 is that their coefficients tend to "decline" from column 4 (type-1 application) to column 5 (type-1 granted), whereas the other, more domestic firms' coefficients tend to "increase." One possibility is that their patent applications are treated differently from domestic firms'; another possibility is that their patent applications are simply different, partly because China is not necessarily their "default" place to file for patent protection.

HMT and foreign firms' numbers look different in columns 2 and 3 as well. Type-4 patents at these firms are more closely related to TFP than at domestic firms, but show no statistically significant relation to new products. Likewise, type-3 patents at HMT firms carry positive and statistically significant coefficient estimate with TFP but not with new products. This feature could be a reflection of our earlier finding in Table 8 that HMT firms showed the lowest inclination to report "new products."

In all of these observations above, an obvious question is whether these different "responsiveness" of patents to TFP and new products is driven primarily by intra- or inter-firm variation. Another, somewhat related question is whether and how these patterns change when we use a finer categorization of domestic firms, according to their privatization trajectories.

5 Conclusion

We have investigated privatization and innovation in China by asking who innovates in China, in what sense (i.e., TFP, new-product introduction, and patent applications), and how these measures of innovation varied with the firms' public/private-sector status.

At the current stage, we have five main findings. First, our ACF estimates of TFP suggest domestic private and mixed-ownership firms have finished their productivity catch-up with foreign firms. SOEs have also closed some of the gap with foreign firms, although their TFP growth lagged behind those of mixed and private firms. These patterns seem consistent with some of the anecdotal evidence that we mentioned in the introduction. Of course, these categorical averages mask the diversity of firms and products within each industry and ownership type, and other qualitative differences may still exist and persist. Nevertheless, the overall trend indicate remarkable achievements.

Second, process and private innovations appear complementary to each other, which is consistent with Athey and Schmutzler's (1995) prediction. Third, type-1 or "invention" patents exhibit strong positive correlation with the measures of process and product innovations. The high fit of type-1 patent regressions suggests firms' application behavior in this category are more "rationalizable" than those in the other two categories (i.e., "design" and "utility" patents).

Fourth, patenting behavior is heterogeneous across ownership types. SOEs and HMT firms' patents are most closely correlated with process innovation, whereas mixed, private, and foreign firms' patents seem more closely associated with product innovation. These patterns are broadly consistent with the anecdotal evidence that SOES employ top scientists and engineers but do not introduce attractive new products, whereas some of the most successful private firms from China have achieved international recognition in high-tech industries.

Fifth, mixed and private firms' superior performance in TFP growth as well as their patenting behavior's close correlation with new-product introductions suggest privatization's positive impact on innovation. The gradual and selective nature of the overall privatization process deserves more formal and in-depth analysis, and hence we plan to advance this research project in this direction.

Appendix

This appendix contains four tables. The first three are the OLS versions of regressions in section 4, and the fourth is a version of Table 9 with the TFP growth rates on RHS. The results are similar to our baseline versions in the main text.

Table 10: Productivity (OLS) and Revenue from "New Products"

Dependent variable: Fraction of revenue from "new products"	(1)	(2)	(3)	(4)	(5)	(6)
Productivity ($\hat{\omega}_{it}$) × SOE	.0054*	.0015	.0052*	.0056	.0010	.0008
	(.0029)	(.0029)	(.0028)	(.0036)	(.0036)	(.0036)
Productivity ($\hat{\omega}_{it}$) × Mixed	.0223***	.0156***	.0203***	.0301***	.0220***	.0238***
	(.0022)	(.0023)	(.0022)	(.0028)	(.0028)	(.0028)
Productivity ($\hat{\omega}_{it}$) × Private	.0098***	.0003	.0066*	.0116***	−.0004	.0033
	(.0036)	(.0037)	(.0036)	(.0044)	(.0045)	(.0044)
Productivity ($\hat{\omega}_{it}$) × HMT	.0170***	.0080**	.0167***	.0216***	.0099**	.0163***
	(.0039)	(.0039)	(.0039)	(.0049)	(.0050)	(.0049)
Productivity ($\hat{\omega}_{it}$) × Foreign	−.0063*	−.0133***	−.0036	−.0043	−.0132***	−.0059
	(.0037)	(.0037)	(.0036)	(.0046)	(.0046)	(.0046)
Productivity growth ($\Delta\hat{\omega}_{it}$) × SOE	–	–	–	−.0010	−.0040	−.0086**
	–	–	–	(.0039)	(.0039)	(.0038)
Productivity growth ($\Delta\hat{\omega}_{it}$) × Mixed	–	–	–	.0154***	.0109***	.0042
	–	–	–	(.0029)	(.0029)	(.0029)
Productivity growth ($\Delta\hat{\omega}_{it}$) × Private	–	–	–	.0105**	.0044	−.0019
	–	–	–	(.0029)	(.0043)	(.0042)
Productivity growth ($\Delta\hat{\omega}_{it}$) × HMT	–	–	–	.0145***	.0074	.0023
	–	–	–	(.0049)	(.0049)	(.0048)
Productivity growth ($\Delta\hat{\omega}_{it}$) × Foreign	–	–	–	−.0021	−.0070	−.0118***
	–	–	–	(.0045)	(.0045)	.0044
Mixed	−.0077***	−.0089***	−0072***	−.0048***	−.0058***	−.0044***
	(.0016)	(.0016)	(.0016)	(.0018)	(.0018)	(.0017)
Private	−.0238***	−.0281***	−.0186***	−.0228***	−.0265***	−.0161***
	(.0018)	(.0018)	(.0018)	(.0020)	(.0020)	(.0020)
HMT	−.0179***	−.0196***	−.0232***	−.0164***	−.0177***	−.0215***
	(.0019)	(.0020)	(.0019)	(.0021)	(.0021)	(.0021)
Foreign	−.0064***	−.0083***	−.0177***	−.0064***	−.0080***	−.0177***
	(.0020)	(.0020)	(.0019)	(.0021)	(.0021)	(.0021)
Size (fitted value of output, $\hat{y}_{it}$)	–	–	.0235***	–	–	.0242***
	–	–	(.0004)	–	–	(.0004)
Constant	.0172***	.0095**	−.2351***	.0163***	.0087**	−.2440***
	(.0035)	(.0038)	(.0053)	(.0038)	(.0040)	(.0057)
Year dummies	*No*	*Yes*	*Yes*	*No*	*Yes*	*Yes*
Industry dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Num. of observations	104,673	104,673	104,673	93,044	93,044	93,044
Adjusted R^2	.0518	.0540	.0895	.0530	.0551	.0913

Note: Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Columns 4, 5, and 6 use the lagged productivity levels and the lagged predicted outputs.

Table 11: Productivity (OLS), "New Products", and Patents (Negative Binomial Regression)

Dependent variable: Patent application count	(1) All types	(2) Type 4 (utility)	(3) Type 3 (design)	(4) Type 1 (invention)	(5) Type 1 granted
Productivity ($\hat{\omega}_{it}$) × SOE	.6472***	.5046	.8929***	.9782***	1.1084***
	(.1743)	(.3083)	(.1946)	(.2618)	(.3108)
Productivity ($\hat{\omega}_{it}$) × Mixed	.6560***	.6105***	.8157***	.6381***	.8337***
	(.1032)	(.1955)	(.1193)	(.1379)	(.1643)
Productivity ($\hat{\omega}_{it}$) × Private	1.6300***	1.7819***	.5101**	.4502	.2224
	(.2000)	(.3686)	(.2042)	(.3107)	(.4011)
Productivity ($\hat{\omega}_{it}$) × HMT	.0163	−.2458	.5525***	.8276***	.7595***
	(.1748)	(.3121)	(.2109)	(.2527)	(.2958)
Productivity ($\hat{\omega}_{it}$) × Foreign	.2037	.0208	.4759**	.8894***	.8741***
	(.1614)	(.2781)	(.2120)	(.2628)	(.3126)
New product revenue (%)× SOE	1.0934***	.9019	.9994***	1.4700***	1.4957***
	(.3364)	(.6623)	(.3080)	(.3424)	(.3972)
New product revenue (%)× Mixed	1.7796***	1.2006***	2.0385***	1.7947***	1.9264***
	(.1890)	(.3308)	(.1748)	(.1845)	(.2029)
New product revenue (%)× Private	1.0836***	1.1028**	1.4001***	1.8106***	1.9454***
	(.2956)	(.5075)	(.3188)	(.3340)	(.3956)
New product revenue (%)× HMT	.0883	.0064	.2795	1.4400***	1.0304**
	(.3248)	(.5856)	(.3369)	(.3593)	(.4316)
New product revenue (%)× Foreign	1.0432***	.3967	1.0701***	1.7548***	1.6055***
	(.2798)	(.4739)	(.1090)	(.2709)	(.3059)
Mixed	.1672**	.4029***	.0049	.1018	.1168
	(.0787)	(.1419)	(.0884)	(.1123)	(.1339)
Private	.2802***	.7637***	−.2403**	−.2116	−.2488
	(.0915)	(.1634)	(.1045)	(.1400)	(.1726)
HMT	.4992***	.9537***	.1930*	.0289	−.0185
	(.0909)	(.1620)	(.1061)	(.1399)	(.1706)
Foreign	−.0255	.3597**	−.1848*	−.4199***	−.5017***
	(.0930)	(.1643)	(.1090)	(.1418)	(.1705)
Size (fitted value of output, $\hat{y}_{it}$)	.7993***	.7494***	.8413***	.9460***	9477***
	(.0161)	(.0298)	(.0184)	(.0197)	(.0226)
Constant	−13.084***	−13.1047	−15.360***	−17.104***	−17.388***
	(.2691)	(.4542)	(.4050)	(.4002)	(.4614)
Year dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes
α	26.7293	85.8232	16.5355	14.4733	14.2721
	(.5376)	(2.6554)	(.5025)	(.5956)	(.7614)
Log likelihood	−28,672	−13,109	−15,854	−9,785	−6,643
Num. of observations	104,673	104,673	104,673	104,673	104,673
Psuedo R^2	.1057	.0663	.1638	.2516	.2734

Note: Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Columns 4, 5, and 6 use the lagged productivity levels and the lagged predicted outputs.

Table 12: Productivity (OLS), "New Products", and Patents (continued)

Dependent variable: Patent application count	(1) All types	(2) Type 4 (utility)	(3) Type 3 (design)	(4) Type 1 (invention)	(5) Type 1 granted
Lagged productivity ($\hat{\omega}_{it-1}$) $\times$ SOE	.7081***	.3496	1.1374***	1.2321***	1.3781***
	(.2025)	(.3403)	(.2399)	(.3256)	(.3802)
Lagged productivity ($\hat{\omega}_{it-1}$) $\times$ Mixed	.6668***	.6473***	.8993***	.5545***	.7052***
	(.1272)	(.2408)	(.1410)	(.1697)	(.1988)
Lagged productivity ($\hat{\omega}_{it-1}$) $\times$ Private	1.3796***	1.3949***	.1787	$-.0041$	$-.3606$
	(.2193)	(.3994)	(.2447)	(.3392)	(.4221)
Lagged productivity ($\hat{\omega}_{it-1}$) $\times$ HMT	$-.1516$	$-.5744$	.6281**	.7977***	.6242*
	(.2084)	(.3687)	(.2447)	(.3105)	(3629)
Lagged productivity ($\hat{\omega}_{it-1}$) $\times$ Foreign	.1546	$-.0991$	.0987	1.1697***	1.4617***
	(.1948)	(.3399)	(.2579)	(.3139)	(.3749)
Productivity growth ($\Delta\hat{\omega}_{it}$) $\times$ SOE	$-.2984$	$-.1843$	$-.0858$	.2416	.1897
	(.2351)	(.4402)	(.2510)	(.3090)	(.3630)
Productivity growth ($\Delta\hat{\omega}_{it}$) $\times$ Mixed	.1632	.2618	.1987	.1066	.2581
	(.1381)	(.2778)	(.1541)	(.1715)	(.1995)
Productivity growth ($\Delta\hat{\omega}_{it}$) $\times$ Private	1.5933***	2.1924***	.1408	.3114	.2653
	(.2700)	(.5522)	(.2282)	(.2997)	(.3486)
Productivity growth ($\Delta\hat{\omega}_{it}$) $\times$ HMT	$-.4336$*	$-.6150$	$-.0654$	.2320	.3338
	(.2237)	(.3979)	(.2501)	(.2892)	(.3374)
Productivity growth ($\Delta\hat{\omega}_{it}$) $\times$ Foreign	$-.3260$	$-.3410$	$-.0421$	$-.3243$	$-.4979$
	(.2101)	(.3931)	(.2574)	(.3115)	(.3649)
New product revenue (%)$\times$ SOE	1.2336***	1.1176	1.0713***	1.5538***	1.5111***
	(.3641)	(.7374)	(.3283)	(.3602)	(.4166)
New product revenue (%)$\times$ Mixed	1.7524***	1.3271***	1.9456***	1.8729***	2.0378***
	(.1936)	(.3430)	(.1790)	(.1884)	(.2071)
New product revenue (%)$\times$ Private	1.1403***	1.1298**	1.4157***	1.8460***	1.9596***
	(.3012)	(.5247)	(.3215)	(.3375)	(.3986)
New product revenue (%)$\times$ HMT	.3190	.2614	.4502	1.5529***	1.1216**
	(.3383)	(.6200)	(.3494)	(.3688)	(.4393)
New product revenue (%)$\times$ Foreign	1.0867***	.4087	1.0047***	1.7748***	1.7025***
	(.2976)	(.5054)	(.2997)	(.2791)	(.3168)
Mixed	.1760**	.4256***	.0268	.1188	.1164
	(.0839)	(.1540)	(.0937)	(.1172)	(.1391)
Private	.2915***	.7555***	$-.1750$	$-.1238$	$-.1992$
	(.0962)	(.1749)	(.1090)	(.1428)	(.1754)
HMT	.4848***	.9740***	.1581	.0535	$-.0474$
	(.0965)	(.1744)	(.1123)	(.1451)	(.1763)
Foreign	.0109	.4215**	$-.0991$	$-.4494$***	$-.6516$***
	(.0985)	(.1764)	(.1146)	(.1502)	(.1835)
Size (lagged fitted value of output, $\hat{y}_{it-1}$)	.8126***	.7605***	.8577***	.9675***	.9718***
	(.0171)	(.0325)	(.0193)	(.0207)	(.0237)
Constant	-12.987***	-13.059***	-15.446***	-17.146***	-17.470***
	(.2786)	(.4836)	(.4361)	(.4013)	(.4627)
Year dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
α	26.3831	86.4825	16.2985	14.5201	14.1943
	(.5439)	(2.7655)	(.5060)	(.6010)	(.7611)
Log likelihood	$-26,896$	$-12,080$	$-14,934$	$-9,465$	$-6,424$
Num. of observations	93,044	93,044	93,044	93,044	93,044
Psuedo R^2	.1036	.0648	.1622	.2473	.2707

Note: Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 13: Productivity (ACF), "New Products", and Patents (continued)

Dependent variable: Patent application count	(1) All types	(2) Type 4 (utility)	(3) Type 3 (design)	(4) Type 1 (invention)	(5) Type 1 granted
Lagged productivity ($\hat{\omega}_{it-1}$) × SOE	.7750***	.5922***	.7736***	1.0340***	.9956***
	(.0539)	(.1046)	(.0599)	(.0782)	(.0901)
Lagged productivity ($\hat{\omega}_{it-1}$) × Mixed	.7616***	.7081***	.7127***	.8460***	.8355***
	(.0380)	(.0704)	(.0428)	(.0480)	(.0556)
Lagged productivity ($\hat{\omega}_{it-1}$) × Private	.6850***	.6110***	.6084***	.8564***	.8966***
	(.0450)	(.0737)	(.0570)	(.0686)	(.0862)
Lagged productivity ($\hat{\omega}_{it-1}$) × HMT	.8244***	.7952***	.7168***	.9163***	.8590***
	(.0524)	(.0909)	(.0619)	(.0721)	(.0823)
Lagged productivity ($\hat{\omega}_{it-1}$) × Foreign	.7847***	.8434***	.5515***	.7792***	.7759***
	(.0490)	(.0879)	(.0553)	(.0612)	(.0712)
Productivity growth ($\Delta\hat{\omega}_{it}$) × SOE	−.0565	−.3977	−.0349	.3527	.3732
	(.1541)	(.3118)	(.1511)	(.2196)	(.2440)
Productivity growth ($\Delta\hat{\omega}_{it}$) × Mixed	.0817	.1367	−.0390	−.1802**	−.2090**
	(.0770)	(.1578)	(.0867)	(.0857)	(.0965)
Productivity growth ($\Delta\hat{\omega}_{it}$) × Private	.0212	−.1333	−.2796**	−.0655	−.0571
	(.1003)	(.1752)	(.1176)	(.1538)	(.1986)
Productivity growth ($\Delta\hat{\omega}_{it}$) × HMT	.2437**	.2550	−.1215	.1106	.1112
	(.1023)	(.1759)	(.1129)	(.1537)	(.1917)
Productivity growth ($\Delta\hat{\omega}_{it}$) × Foreign	.0023	−.0618	−.1375	−.3045***	−.3557***
	(.0980)	(.1893)	(.1091)	(.1116)	(.1241)
New product revenue (%)× SOE	1.5970***	1.5617*	1.4140***	1.8130***	1.6363***
	(.3960)	(.8111)	(.3502)	(.3807)	(.4376)
New product revenue (%)× Mixed	1.6743***	1.2326***	1.8992***	1.7713***	1.9566***
	(.1986)	(.3546)	(.1815)	(.1917)	(.2103)
New product revenue (%)× Private	1.0914***	1.1138**	1.3738***	1.8364***	1.9835***
	(.3039)	(.5433)	(.3250)	(.3386)	(.4026)
New product revenue (%)× HMT	.3244	.3238	.5872	1.5680***	1.1461***
	(.3509)	(.6564)	(.3586)	(.3721)	(.4412)
New product revenue (%)× Foreign	1.4646***	.8927	1.2417***	1.8822***	1.7698***
	(.3160)	(.5676)	(.3126)	(.2765)	(.3155)
Mixed	.3515*	.2151	.3855*	.9911***	.8639**
	(.1984)	(.3826)	(.2182)	(.3241)	(.3653)
Private	.8084***	.9605**	.6420**	.6650*	.2215
	(.2307)	(.4165)	(.2651)	(.3957)	(.4784)
HMT	.3347	.3913	.5090*	.6377	.5858
	(.2509)	(.4512)	(.2969)	(.4092)	(.4627)
Foreign	−.0736	−.5260	.8994***	.7496*	.4084
	(.2548)	(.4700)	(.2876)	(.3911)	(.4483)
Size (lagged fitted value of output, $\hat{y}_{it-1}$)	.8327***	.7838***	.9179***	.9816***	.9908***
	(.0199)	(.0396)	(.0222)	(.0228)	(.0262)
Constant	−13.487***	−13.145***	−17.084***	−18.069***	−18.422***
	(.3844)	(.7147)	(.5330)	(.5200)	(.6373)
Year dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
α	25.4475	86.0491	15.5813	13.8564	13.6289
	(.5456)	(2.8936)	(.4984)	(.5813)	(.7434)
Log likelihood	−24,748	−10,862	−13,754	−9,125	−6,191
Num. of observations	81,413	81,413	81,413	81,413	81,413
Psuedo R^2	.1034	.0645	.1640	.2439	.2676

Note: Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

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