American Economic Review 2020, 110(4): 1055–1103
https://doi.org/10.1257/aer.20171732

Industrial Espionage and Productivity†

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In this paper, we investigate the economic returns to industrial espionage. We show that the flow of information provided by East German informants in the West over the period 1970–1989 led to a significant narrowing of sectoral TFP gaps between West and East Germany. These economic returns were primarily driven by relatively few high-quality pieces of information and particularly large in sectors closer to the West German technological frontier. Our findings suggest that the East-to-West German TFP ratio would have been 13.3 percent lower at the end of the Cold War had East Germany not engaged in industrial espionage in the West. (*JEL* L16, N44, O33, O38, O47, P24)

Despite the rich history of illicit technology transfer and its significant contemporary importance, industrial espionage and its associated costs and benefits have received little attention in the economic literature.[1] Undoubtedly, the secret nature

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† Go to https://doi.org/10.1257/aer.20171732 to visit the article page for additional materials and author disclosure statements.

[1] While "industrial espionage" and "economic espionage" are often used interchangeably, some authors draw a distinction between them with industrial espionage referring specifically to activities conducted by individual companies against their competitors for commercial purposes and economic espionage referring to activities in the economic domain conducted on behalf of foreign governments and for reasons that are not exclusively commercial. Because of the distinct focus on different industry sectors in our analysis, we have followed the common practice in the context of East German scientific-technical espionage of using the term "industrial espionage" throughout the paper (see Müller, Süß, and Vogel 2009). Note that from a legal point of view, there is no uniform definition of what constitutes the punishable offense of espionage. In the United States, the Economic Espionage Act of 1996 defines economic espionage as "the theft or misappropriation of a trade secret with the intent or knowledge that the offense will benefit any foreign government, foreign instrumentality, or foreign agent." In Germany, espionage is typically

of the practice obscures its economic significance which is believed to be considerable. For example, industrial espionage is currently estimated to cost the US economy around \$19 billion per year and the German economy around 11.8 billion euros per year, both figures from the lower end of a wide range of available estimates.[2] Compared to the costs, the economic benefits accruing to those countries actively engaging in industrial espionage are even more opaque. However, its persistent and widespread use as a channel for technology transfer suggests that these benefits are substantial.

In this paper, we provide the first comprehensive analysis of the relationship between state-sponsored industrial espionage and technological progress. The historical setting is the Cold War period in which industrial espionage became instrumental for economic development as the communist bloc attempted to catch up with the capitalist world's technological advantage. The centerpiece of our study is a dataset, the so-called SIRA, that comprises the entire stock of information East German foreign intelligence sources gathered abroad during the period 1970 to 1989. This unique database includes detailed information on 189,725 individual pieces of information received by the East German Ministry for State Security (MfS, commonly referred to as the *Stasi*), including their precise date of receipt, the code names of their sources, and a list of keywords describing each item's content. To operationalize this wealth of data, we use the keywords provided to attribute each piece of information to the appropriate industry sector(s). We then merge the aggregated sector-specific information flows to sectoral total factor productivity (TFP) measures which we compute from time series data on sectoral gross value added, employment, and gross fixed capital investment. In our main estimation equation, we regress changes in sectoral log TFP gaps between West and East Germany (equivalent to differences in TFP growth rates) on past inflows of sector-specific information generated by industrial espionage, controlling for direct measures of R&D activity in both parts of Germany and their initial distance to the technological frontier. Our estimates thus speak directly to the question in how far industrial espionage allowed the East German economy to keep up with technological progress in the West.

Our results provide evidence of significant economic returns to industrial espionage, indicating an important role of international knowledge flows for productivity growth in laggard countries. A 1 standard deviation increase in the inflow of information results in a 7.3 percentage point (4.9 percent) decrease of the log TFP gap and a 5.5 percentage point (4.3 percent) decrease in the log output per worker gap between West and East Germany. We also provide complementary evidence for a positive effect of industrial espionage on a purely quantity-based measure of output and on the number of new goods produced in East Germany. Furthermore, we show that industrial espionage tended to crowd out investments in regular overt R&D in East Germany. To address potential endogeneity concerns, we employ two distinct instrumental variable strategies. The first one utilizes information generated by informants who were already active at the beginning of the sample period in a

punishable under §99 StGB according to which anyone is subject to prosecution who "discloses or delivers facts, objects or findings to a foreign intelligence service, or agrees to such activity."

[2] Sources: Munsey (2013) for the United States and Corporate Trust (2014) for Germany.

shift-share-type setting. The second exploits the sudden disappearance of certain informants as providers of information as an exogenous source of variation. Both instruments lead to results that are somewhat larger in magnitude than our baseline ordinary least squares (OLS) estimates.

In a series of robustness checks, we show that our findings are not exclusively driven by the very prominent IT sector and robust to variations in the way observations are weighted and pieces of information assigned to different sectors. We also provide evidence that changes in the calibration of the key parameters underlying our sectoral TFP measures have little impact on our estimates. Through a series of placebo tests, we further demonstrate that our main results are not driven by a spurious correlation between the regressor of interest and the dependent variable, a possibility given their specific functional forms. When testing the robustness of our findings to alternative functional forms, for example by changing the applied normalization or using raw instead of scaled measures of espionage inflows, the results are more mixed. While generally maintaining the expected sign, the estimates become statistically insignificant on a number of occasions, especially in the IV estimations. Contrary to our baseline model, these specifications have no theoretical foundation, but this lack of significance does indicate some sensitivity of our findings to alternative functional form assumptions.

Analyzing different dimensions of heterogeneity, we document that the positive effect on East German productivity growth is primarily driven by relatively few high-quality pieces of information and that industrial espionage was particularly effective in those sectors that were closest to the West German technological frontier. We conclude by running a counterfactual simulation of how East German TFP would have evolved in the absence of industrial espionage, showing that it had overall a noticeable but quantitatively modest mitigating effect on the productivity gap with West Germany. Our findings suggest that the ratio of East-to-West German TFP, which amounted to 21.8 percent in 1989, would have been 13.3 percent lower (so 18.9 percent) in the absence of industrial espionage. For some sectors, however, we find that industrial espionage was vital to avoid a significant further opening of the technological gap. In the electronics sector, for example, the already low East German TFP level relative to West Germany's of 12.0 percent in 1989 would have been 39.2 percent lower (7.3 percent) if East Germany had not been so prolific in acquiring relevant technological information in this sector through its espionage activities in the West. A tentative cost-benefit analysis indicates that the net return of industrial espionage was substantial, with annual benefits of the order of 10.1 billion euros contrasting with annual running costs of around 11.0 million euros.

Besides providing the first empirical assessment of the role of industrial espionage for technological progress, our paper speaks to several existing literatures in economics. Most importantly, since industrial espionage inherently involves the flow of technological knowledge from the targeted to the perpetrating country, our findings contribute to the extensive work on international technology diffusion.[3] This literature has focused either directly on international R&D spillovers (e.g., Jaffe, Trajtenberg, and Henderson 1993; Griffith, Harrison, and Van Reenen 2006; Coe, Helpman, and

[3] For overviews of this literature, see Jones (2005), Keller (2010), and Comin and Mestieri (2014).

Hoffmaister 2009) or studied the role of international trade (e.g., Eaton and Kortum 2002; Cameron, Proudman, and Redding 2005; Buera and Oberfield 2016), foreign direct investment (e.g., Javorcik 2004; Keller and Yeaple 2009; Guadalupe, Kuzmina, and Thomas 2012), and international migration (e.g., Hornung 2014; Moser, Voena, and Waldinger 2014) as possible conduits of knowledge spillovers. Contrary to most of this work, we observe knowledge flows directly which allows a more accurate assessment of their importance for productivity growth. Due to the different markets in which East and West Germany operated at the time, the spillover effects we estimate are also less likely to be confounded by countervailing business-stealing effects through product market rivalry, a lingering identification problem in past studies on the impact of R&D spillovers on economic growth (Bloom, Schankermann, and Van Reenen 2013; Fons-Rosen et al. 2017).

Viewing industrial espionage as a means of acquiring new scientific-technical knowledge, our study also relates to the literature on the role of innovation in explaining productivity growth (e.g., Aghion and Howitt 1992; Hall, Mairesse, and Mohnen 2010). In analyzing the heterogeneous effects of industrial espionage across East German industries and its impact on East Germany's own R&D efforts, we also touch on the literatures on absorptive capacity (e.g., Aghion and Jaravel 2015) and the role of the distance to the technological frontier for aggregate productivity growth, technology adoption, and innovation (e.g., Griffith, Redding, and Van Reenen 2004; Acemoglu, Aghion, and Zilibotti 2006; Comin and Hobijn 2010).

Apart from the broader innovation literature, our analysis also contributes to the literature studying the social and economic consequences of covert activities and secrecy. In a recent study, Lichter, Löffler, and Siegloch (2016) exploits discontinuities at state borders within East Germany to show that higher levels of Stasi surveillance during the 1980s led to lower levels of social capital and worse economic outcomes in the post-unification period. Other examples for the adverse effects of secrecy come from the archival study of the former Soviet Union's intelligence agency, the KGB, revealing for instance that secrecy incurs broad efficiency costs in the economy (Harrison 2008). In the US context, declassified intelligence documents have been used to show that CIA-supported coups led to significant stock market gains for firms with a particular interest in regime change (Dube, Kaplan, and Naidu 2011) and that imports from the United States increased systematically in those countries in which the CIA successfully helped install a new leadership (Berger et al. 2013). Finally, in studying the effects of an arguably widespread but generally unobservable economic activity, our paper also has some connection to the literature on the shadow economy, which has provided insights into similarly elusive activities such as tax evasion (e.g., Kleven et al. 2011), corruption (e.g., Olken 2007), and illicit trade (e.g., Fisman and Wei 2009).

Outside of economics, there is of course a more extensive literature on espionage by historians, often focusing on specific case studies or the successes and failures of individual spies (e.g., Friis, Macrakis, and Müller-Enbergs 2009). Regarding East German espionage in the West, Herbstritt (2007) provides a comprehensive picture of the recruitment strategies of the Stasi and the social structure of its network of informants, complementing the extensive work on the Stasi and its foreign intelligence branch by Müller-Enbergs (1996, 1998, 2011). Macrakis (2008) comes closest to the type of question we analyze in this paper, arguing that the Stasi's scientific-technical intelligence activities were ultimately a failure as the secretive nature of high-tech espionage clashed with the openness required for successful scientific development. Yet as late as 1989, East Germany was seen by some as "communism that works" and "the communist world's high-technology leader… its capital goods known for quality workmanship."[4] Our main results show that once the entirety of the information flows from the West are taken into account, East Germany's industrial espionage program can by all means be viewed as a success.

The rest of the paper is organized as follows. Section I provides the historical context in which East Germany engaged in industrial espionage in the West. Section II describes the various data sources used in the paper. Section III presents two case studies that illustrate the process through which industrial espionage affected production in East Germany. Section IV introduces the empirical framework and estimation strategy. Section V presents the main results as well as further complementary analysis. Section VI concludes the paper.

I. Historical Background

East German industrial espionage was to a large extent a response to the West's implementation of economic containment policies at the onset of the Cold War. Already shortly after the end of World War II, Western Bloc countries led by the United States imposed a trade embargo on their Eastern Bloc counterparts, initially focusing on restricting the trade of arms and weapons technology. Over the following decades, the Coordinating Committee for Multilateral Export Controls (CoCom) served as a tool for the West to implement ever more stringent export controls on goods bound for the communist East. Increasingly, these included not just goods from the military and nuclear sectors but also industrial "dual-use" products that could, at least in principle, be used for military purposes. As the trade embargo against the communist bloc intensified, East Germany came to rely increasingly on its industrial espionage to keep up with the West.

The Stasi's industrial espionage was conducted predominantly under its foreign intelligence unit (*Hauptverwaltung Aufklärung*, HVA), led by the famous spy chief Markus Wolf. The branch in charge of gathering scientific-technical information in the West was the Sector for Science and Technology (*Sektor Wissenschaft und Technik*, SWT), which by the end of 1988 comprised around 260 full-time staff members and consisted of three specialized departments responsible for the acquisition of information in the areas of Energy, Biology and Chemistry (*Abteilung XIII*), Electronics and Electrical Engineering (*Abteilung XIV*), and Machine Building and Embargo Goods (*Abteilung XV*), one department responsible for the evaluation of all incoming information (*Abteilung V*), and a number of smaller working groups (Müller-Enbergs 1998).

For the collection of scientific-technical information, the Stasi relied on an extensive network of informants in Western Bloc countries, especially West Germany. Knabe (1999), Müller-Enbergs (1998), and Herbstritt (2007) provide insightful information about the recruitment, motivation, and social background of the

[4] "East Germany Losing Its Edge," *New York Times*, May 15, 1989, https://www.nytimes.com/1989/05/15/business/east-germany-losing-its-edge.html.

Stasi's collaborators in West Germany. More than half of the informants still active at the end of the 1980s were initially brought to the Stasi's attention as potential recruitment targets by other already active informants. In contrast, informants who approached the Stasi on their own initiative constituted only a relatively minor fraction of less than 5 percent. Internal Stasi documents further show that 60 percent of the informants were recruited primarily due to their political-ideological convictions, 27 percent due to material interests and only less than 1 percent "under pressure." According to Herbstritt (2007), a simple informant in the West could expect monthly payments of between 100 and 500 Deutsche Mark plus the reimbursement of expenses, which would represent a moderate top-up of their regular salaries. For high profile informants, however, these regular payments could be substantially higher, reaching amounts of several thousand Deutsche Mark per month. In terms of socioeconomic background, most of the informants involved in industrial espionage in the West were middle-aged male salaried employees, predominantly engineers or employees with science degrees, although a number of sources also worked in personnel departments or as businessmen. These informants were not necessarily leaders in their field or heads of departments but often more mid-ranking employees like engineer Dieter Feuerstein (codename: Petermann) at MBB, who passed on top-secret military plans, Peter Alwardt (codename: Alfred), who worked as an engineer at AEG/Telefunken, and Peter Köhler (codename: Schulze), who worked for Texas Instruments.

In terms of scientific-technical fields targeted, the Stasi generally cast a wide net. Of broad interest were, for example, processes for a more economical use of energy or more efficient processing techniques for raw materials (Müller-Enbergs 1998). A particularly important role in the Stasi's industrial espionage program, however, was given to the electronics sector, especially since the 1970s when the East German political leadership decided to become a world leader in computer technology and started to direct significant resources to the production of microchips and the infiltration of Western electronics companies such as IBM and Siemens. Meanwhile, Western intelligence in East Germany remained by most accounts limited, especially in the economic sector which was technologically behind and therefore not a priority target of Western espionage. As such, the transfer of technologies was overwhelmingly a one-way street.

II. Data

A. *SIRA Data*

Our main data source on the Stasi's industrial espionage activities in the West is the HVA's central electronic database SIRA (*System der Informationsrecherche der Hauptverwaltung Aufklärung*), currently maintained by the Agency of the Federal Commissioner for the Stasi Records (BStU). Within SIRA, subdatabase 11 (*Teildatenbank 11*) comprises records of essentially all scientific-technical information that the Stasi's informants passed on to the HVA during the 1970s and 1980s.[5]

[5] In anticipation of the introduction of SIRA, the HVA started in 1968/1969 to systematically record all incoming information on punched tape, which was then fed into the SIRA database when it was launched in July

Given the historical circumstances, the fact that these data still exist is remarkable. At the beginning of 1990, with political changes sweeping through East Germany, it was decided to disband the Stasi and physically destroy all sensitive information, including all electronic data carriers. By March 19, 1990, "10,611 magnetic tapes, 5,267 disks, 544 removable hard disks, and 80 sacks of loose magnet tape material" had been destroyed, including all data stored in the original SIRA system.[6] However, in the process of a comprehensive data conversion of the entire SIRA system in 1988/1989, the HVA had made copies of the original data which were then overlooked when the Stasi was liquidated. The data from these copies, meticulously reconstructed by the BStU during the 1990s (see Konopatzky 2007), form the basis of the present analysis.

In total, 189,725 pieces of information were recorded in SIRA between 1968 and 1989, corresponding to an annual average inflow of 8,624 items. Online Appendix Figure A1 displays the distribution of this flow of information over time. Throughout the 1970s, the volume of information received per year was declining but started to increase steadily again from 1979 onward, eventually peaking in 1988, the year before the fall of the Berlin Wall and the last year fully covered by SIRA, with a record of 15,658 pieces of information.[7] Given these magnitudes, it is not surprising that not all of the information flow from the West necessarily involved the theft or misappropriation of trade secrets, the legal definition of economic espionage in, for example, the United States today. Instead, a significant fraction of the intelligence received likely referred to information that was publicly available anyway, thus more resembling so-called "competitive intelligence" which is generally considered to be legal. While we do not have a direct way of discerning whether a given piece of information was obtained illegally, internal quality assessments of the Stasi provide some indication about the intrinsic value of each piece of information (see Section VE) which should also reflect the difficulty of obtaining the relevant information.

Upon arrival at the Stasi, specialist internal evaluators created, for each incoming piece of information, an electronic entry in the SIRA database in which they recorded, among other things, the date of arrival of the information, the source of the information, as well as a number of often highly specific keywords to describe the information's content. After this initial documentation, the received material was then passed on to potentially interested parties, typically state-run enterprises or East German research facilities, for further assessment and economic exploitation. Contrary to the electronic data entries in SIRA, the original intelligence delivered (documents, photos, tapes, disks, blueprints, etc.) was destroyed in the process of disbanding the Stasi in early 1990, so that only the data entered into the SIRA system can shed light on the actual content of each piece of information received. In

1974. Industrial espionage on behalf of the Stasi in the West was of course already taking place prior to 1968 but there are no electronic records that would allow us to extend our analysis to this earlier period.

[6] Source: Komitee zur Auflösung des AfNS: Abschlussbericht der Vernichtung der magnetischen Datenträger zu personengebundenen EDV-Projekten des ehemaligen AfNS, vom 19.03.1990, BArch, DO 104.

[7] While the SIRA data do not allow determining the country of origin of a given piece of information, internal documents of the Stasi as well as other historical sources show that West Germany was by far the most important target of the Stasi's espionage activities. According to Müller-Enbergs (2011), 82.7 percent of the informants abroad that were handled by the three principle departments of the HVA's Sector for Science and Technology in December 1988 were located in West Germany.

total, subdatabase 11 comprises 143,005 distinct keywords, 68.5 percent of which are only used once over the entire time period. On average, each piece of information is described by 5.6 distinct keywords but the distribution is skewed to the right, with a median of 5, a ninety-fifth percentile of 10, and a maximum of 145 keywords.

To operationalize these keywords and connect them to the sectoral time series data, we selected in a first step the 2,000 most frequently occurring keywords, which together account for 63.8 percent of all keyword entries in the database, and assigned them to their corresponding sectors. Online Appendix Table A1 lists the 30 most frequently and 10 least frequently used keywords in this subsample, together with their English translations, their frequency in the data, and the sectors to which we allocated them. Examples of frequently used keywords are *Military Technology*, *Electronics*, *Chemistry*, *Microcomputer*, *Metallurgy*, *Optics*, *IBM*, and *Nuclear Power Plant*. Overall, we were able to assign 55 percent of the 2,000 most common keywords to at least one of the 16 sectors for which we have information on output, employment, and investment.[8] After this allocation procedure, the vast majority of the distinct pieces of information in our sample are described by between 1 and 5 sector-specific keywords, and only 18.6 percent are not described by any sector-specific keyword. Online Appendix Table A2 provides a number of concrete examples that illustrate the allocation procedure.

Figure 1 shows the sectoral distribution of the 151,627 pieces of information that could be allocated to at least one of the 16 available sectors over the period 1968 to 1989. In our baseline specification, we count a piece of information as pertaining to a specific sector if it is described by at least one keyword corresponding to that sector. A given information may therefore refer to more than one sector. In line with historical accounts, the sector *Office Appliances*, *Computers, and Electronics* constituted by far the most important sector for industrial espionage, with 100,279 pieces of related information in total, followed by the sectors *Chemicals* (33,409), *Utilities* (23,485), and *Machine Building* (23,152). For our empirical analysis, we drop the early years 1968 and 1969 as well as the final year 1989, since these are only partially covered by the SIRA data.

Looking at the providers of these pieces of information, the SIRA database identifies 2,968 distinct informants based on their assigned registration numbers. Online Appendix Table A3 lists the 20 most productive sources of information over the period 1968 to 1989. However, these top-ranking informants were certainly an exceptional group in terms of the amount of information they generated. Across the whole group of informants, the median and mean inflow of information amounts to only 4 and 52.3 items respectively, reflecting the highly right-skewed distribution illustrated in online Appendix Figure A2. The information provided by most informants throughout their time in the service of the Stasi was thus limited, reflecting the cautious approach by the Stasi in handling its sources as well as the difficulties for most informants to tap into relevant information. Online Appendix Figure A3 depicts the distribution of the first and last active year in which each informant is observed in the data. The left panel suggests that recruitment of new informants was

[8] The remaining 45 percent are either not classifiable (80.9 percent) or refer to other sectors of the economy such as agriculture, construction, automobile repairs and consumer goods, transportation and communication, finance, leasing and public and private services, health, military, or the aerospace industry (19.1 percent).

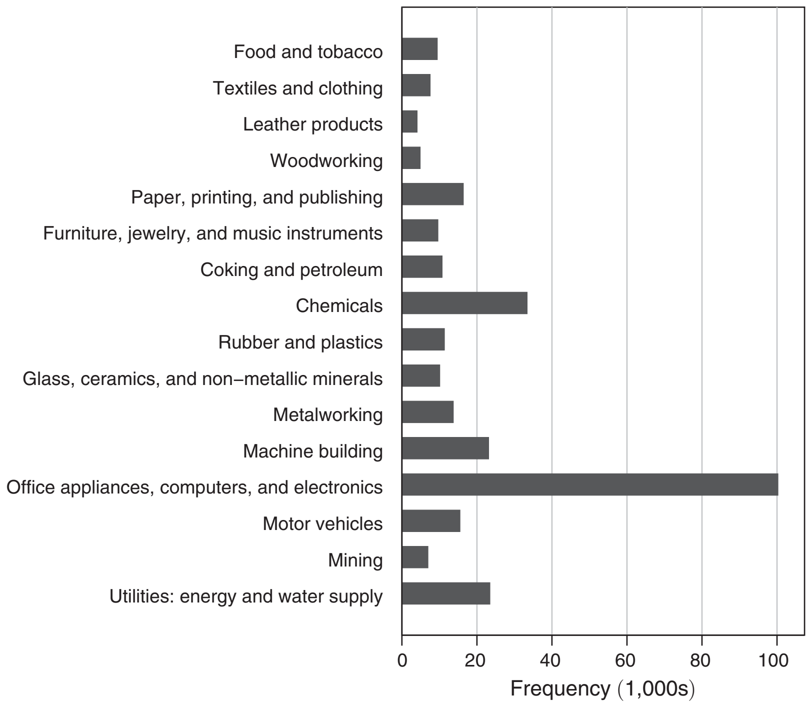

Figure 1. Sectoral Distribution of Information

Note: Figure shows the sector-specific inflows of information received by the HVA between 1968 and 1989.

an ongoing process, with increasing efforts from the early 1980s onward. The right panel shows that informants also continuously ceased to provide further information. We will exploit this fact later on in the construction of one of our instrumental variables.

B. *Industry-Level Data*

The second key data source for our empirical analysis are the sector-specific time series for gross value added, total employment, and gross fixed capital investment constructed by Heske (2009, 2013, 2014). The purpose of this work was to provide a comparable, retrospective accounting of the development of key economic indicators for different industry sectors in West and East Germany over the time period 1950 to 2000. Due to the fundamental differences in economic systems before German unification in 1990, such computations constitute a challenging task, not least because West and East Germany followed different national accounting standards during the pre-unification period.[9]

[9] While West Germany's national accounting was based on the nowadays-standard System of National Accounts (SNA), East Germany applied, together with the Soviet Union and other Eastern Bloc countries, the so-called Material Product System (MPS).

The starting point of Heske's work are the insights gained from the so-called "retroactive accounting project" (*Rückrechnungsprojekt*) which the Federal Statistical Office of unified Germany initiated in 1990. Besides the collection, protection, and documentation of the existing statistical data in the former GDR, the mission of this project included the retroactive computation of key economic indicators based on current methodological concepts and taxonomies. To this end, the Federal Statistical Office followed a bottom-up approach, computing the relevant indicators on the basis of the primary data collected by the East German Statistical Office. This work led to an official publication in 2000 providing detailed information about the production and expenditure side of GDP in the former GDR between 1970 and 1989, expressed in current East German mark.[10]

In a series of subsequent publications, Heske (2005, 2009, 2013), who was actively involved in the retroactive accounting project, builds on these initial findings but makes four important contributions. First, he translates all values of output and investment into constant East German mark relative to the base year 1985. Second, he converts all values into constant 1995 euros, allowing a direct comparison of West and East Germany's economic performance over time. Third, he extends the time horizon to the period 1950 to 1969, for which the existing data basis, however, are significantly more limited. Finally, and crucially for our analysis, he constructs separate time series for 16 distinct economic sectors in both countries. While the West German data are taken directly from the national accounts of the Federal Statistical Office, the procedure to construct the corresponding time series for East Germany is more involved, especially regarding the translation of values into constant East German prices and their subsequent conversion into 1995 euros.

As stated above, the original data series produced by the retroactive accounting project on East German gross value added and gross fixed capital investment were expressed in current East German mark, thus reflecting both changes in quantities and prices. In East Germany's centrally planned economy, these prices were set administratively at regular intervals, reflecting primarily the production costs of a given product and a profit margin that was negotiated between the producers and the responsible state authorities under consideration of economic, political, and social factors.[11] Using comprehensive price information on more than 1,600 individual products collected annually by the East German Statistical Office, Heske is able to trace product-specific price changes over time and thus compute aggregate sector-specific price indices through which gross output, intermediate inputs, and capital investments can be evaluated at prices of the base year 1985. While not representing market prices, this common price basis allows a consistent measurement of the real growth in sector-specific gross value added and gross fixed capital investment over time.

A common problem in the construction of price indices is the handling of new or qualitatively improved products. Because prices in East Germany were set by state authorities under explicit consideration of the presumed utility value of the product, East German price statistics relied on the so-called "link-to-show-no-price-change method" in which price changes between an old product and its replacement product are entirely attributed to quality changes and therefore not reflected in the underlying

[10] Statistisches Bundesamt: Sonderreihe mit Beiträgen für das Gebiet der ehemaligen DDR, Heft 33, 2000.
[11] For a detailed overview of the East German price system during the 1970s and 1980s, see Melzer (1985).

price indices. In the case of East Germany, there is evidence that this led to an underestimation of real price inflation (since the administratively set prices tended to overstate the new products' true utility values) and hence an overestimation of real growth. Based on extensive internal analyses on this issue by the East German Statistical Office, Heske corrects for these biases in the sector-specific price indices, resulting in additional annual price increases of between 0.9 percent and 1.8 percent and thus correspondingly smaller real growth rates. As there remains some uncertainty whether these corrections fully address the measurement issues arising from the introduction of new and upgraded products, we also provide evidence with respect to a purely quantity-based measure of output in the empirical analysis (see Section VD).

The second step in the construction of the East German time series involves the conversion of the output and investment values from constant East German mark to euros of the reference year 1995. A key advantage in this context is the fact that most of the goods produced in the former GDR were observed both priced in East German mark and, after the monetary union on July 1, 1990, in West German deutsche mark. Relating 1989 prices denominated in East German mark to their 1991 counterparts denominated in Deutsche Mark, Heske computes highly differentiated conversion coefficients for both production and intermediate input values, building on previous work by Ludwig, Stäglin, and Stahmer (1996). Based on these coefficients, the existing sector-specific time series on gross value added and capital investment are then translated into constant 1991 deutsche mark and, after a further sector-specific deflation to the reference year 1995, converted into euros. While a common price basis is indispensable for the comparison of West and East German productivity levels, it is largely inconsequential for our main analysis in which we focus on the link between relative productivity growth and industrial espionage. This is relevant as there is some debate about whether the observed prices of East German products in 1991 accurately reflected their true value, given that many of them eventually disappeared from the market.

Because of the historical context, a certain degree of skepticism regarding the informative value of the East German output data is a priori justified. As a subordinate institution, the East German Statistical Office lacked independence from the government and the ruling SED party, which viewed statistical information as a potential tool of agitation and propaganda. Consequently, the reliability of statistical information in the former GDR has been the subject of extensive and controversial discussions. In the context of our study, it is therefore important to emphasize that our sector-specific time series data are constructed from original primary data sources as well as unpublished internal documents of the East German Statistical Office. Most of these sources and documents were at the time labeled as "confidential" and as internal material not subject to politically motivated manipulation, which tended to occur at the final publication stage. Two important studies by the (West German) *Deutsches Institut für Wirtschaftsforschung* (DIW) and the Federal Statistical Office attest to the overall validity of the statistical information in the former GDR, concluding that there are no indications of a systemic tampering with the data and that these, by and large, provide an accurate account of reality.[12]

[12] See Hölder (1992) and DIW (1987).

Assessing the reliability of the data by Heske (2013) is complicated by the fact that there is no other analysis that goes into the same level of detail and studies disaggregated sector-specific developments in East Germany during the relevant time period. However, in earlier work, Heske (2009) constructed similar time series on a more aggregate level following the same basic approach, so a closer look at these figures can provide some indication regarding its plausibility. According to the findings from this study, East Germany's GDP per capita in 1989 amounted to about 56 percent of West Germany's, a figure located in the middle of available estimates (Steiner 2006). If we aggregate across all 16 sectors available in Heske (2013), output per worker in the East German industry in 1989 is about 44 percent of that in West Germany, comparable to the figure of around 40 percent provided by the Federal Statistical Office for the first post-unification years 1991–1994.[13] Another indication of the reliability of Heske's work is the similarity between his constructed measures of value added per worker for individual West German industries and the corresponding figures taken from the EU KLEMS Growth and Productivity Accounts illustrated in online Appendix Figure A4. Apart from the *coking and petroleum* sector, where the EU KLEMS data show significantly higher productivity levels than the Heske data due to a different aggregation of individual subsectors, there is a high level of agreement between the two data sources, both in terms of levels and dynamic patterns over time. Finally, in contrast to other studies that have tried to retrospectively estimate aggregate economic indicators for East Germany at constant prices, Heske is the only one who bases his work on the original primary data, building on the extensive groundwork carried out during the official retroactive accounting project. We are therefore confident that our industry-level data provide an overall good reflection of the key economic developments in East Germany over the time period considered.

C. *Patent Data*

To isolate the impact of industrial espionage on productivity, it is important to control for other fundamental drivers of productivity, especially R&D investments which have been shown to be particularly relevant for economic growth. Unfortunately, there are no consistent data series available of sector-specific R&D investments in West and East Germany for the time period 1970 to 1989. To proxy for both countries' own R&D activities, we therefore use the annual number of sector-specific patent applications. For West Germany, we obtain these from the DEPATISnet database of the German Patent Office and the EPAB database of the European Patent Office by summing the annual number of West German patent applications across all IPC's categories belonging to one of our 16 industry sectors.[14]

[13] Source: "Bruttoinlandsprodukt, Bruttowertschöpfung in den Ländern und Ost-West-Großraumregionen Deutschlands 1991 bis 2010," *Volkswirtschaftliche Gesamtrechnungen der Länder*, Reihe 1, Band 1, 2011.

[14] The European Patent Office has accepted patent applications for its member states since 1978. The total number of applications is the sum of all A-, B1-, and C1-Schriften recorded by the German Patent Office and all A1 and A2 documents recorded by the European Patent Office. If a given IPC pertains to more than one industry sector, we assign fractions of the corresponding numbers of patents to each industry using weights taken from the MERIT concordance table IPC-ISIC (revision 2) provided by Verspagen, van Moergastel, and Slabbers (1994).

The source of our East German patent data are formerly confidential publications summarizing the annual innovation activities in the GDR (*Ergebnisse der Erfindertätigkeit und Schutzrechtsarbeit*) between 1970 and 1989 which were originally published by the East German Statistical Office and are now available at the German Federal Archives in Berlin. For each year and state combine, these publications report a number of innovation-related outcomes, including the number of patent applications. To construct sector-specific outcomes, we assign each state combine to one of our 16 industry sectors, which is straightforward since combines were organized along sectoral lines, and sum the number of patent applications across combines operating in the same sector. Online Appendix Figure A5 shows the number of patent applications by sector in West and East Germany for the period 1970 to 1989.

To assess whether these patent applications can serve as a reasonable proxy for innovation activity in East Germany, it is important to understand the institutional context (Wiessner 2013). With the introduction of the "economic patent" (*Wirtschaftspatent*) in 1950, the nature of patenting in East Germany started to deviate substantially from that in West Germany and other market-oriented economies. In particular, following the Soviet example, the exploitation rights granted by an economic patent, essentially the only type of patent available for domestic inventors, were held by the state rather than the individual inventor, reflecting the socialist idea that scientific-technical innovations should benefit society as whole and not just individual producers. Concerned about the potential effects this might have on innovation incentives, East German patent law stipulated that the inventors behind an economic patent had the right to a one-off financial compensation depending on the economic benefit derived from the patent, which could vary between 75 and 200,000 East German mark. While this regulation did a reasonable job in aligning the incentives of inventors, researchers, and developers with those of the central planning authorities, it did little in incentivizing state-owned firms to modernize in the absence of market pressures, which was viewed as one of the main shortcomings in East Germany's patent system after 1950.

As a founding member of the World Intellectual Property Organization, East Germany otherwise adhered to many common international IP practices, offering for example a traditional "exclusive patent" (*Ausschließungspatent*) to foreign applicants in order to benefit from international knowledge transfer and protecting its own intellectual property against foreign competitors through patenting at home and abroad. Despite the peculiarities inherent to the system, we therefore consider East German patent applications a reasonable proxy for R&D activities across sectors and over time.

D. *Statistical Yearbook Data*

To complement our main empirical analysis based on the industry-level data by Heske, we compile data from the East German Statistical Yearbooks (editions 1971–1990) on the physical quantities of all goods consistently produced throughout the period 1970 to 1989. In total, there are 104 distinct products belonging to 15 of the 16 sectors included in our analysis, with quantities typically measured in metric tonnes, units, or square meters.[15] We use the same data to construct proxies for the

[15] Each statistical yearbook reports product-specific output for a number of previous years. In the case of multiple observations for a given product and year, we take the average across available observations.

number of distinct products manufactured in a given year. To extract as much information as possible, we assume that if a given product is listed only intermittently in the statistical yearbooks, say in year t and then again in year $t + 3$, it was also produced in the intermediate years $t + 1$ and $t + 2$. While the lists of products included in the different yearbooks do not represent East Germany's full output portfolio, they are likely to comprise the most important items and thus provide at least some information on relative shifts in output mix between sectors and over time.

E. *Trade Data*

To construct measures of sectoral import intensity, we use trade data from the World Trade Flows 1962–2000 (WTF) collected by Feenstra et al. (2005). The data comprise bilateral trade flows disaggregated at the 4-digit SITC (revision 2) level which we convert to the ISIC (revision 2) system of our industry data using the concordance constructed by Muendler (2009). We focus on import values since information on physical quantities is not available until 1984. In the WTF, priority is generally given to bilateral trade flows as reported by the importing countries as these are considered to be more accurate than those reported by the exporters. For East Germany, this information is not available so that the WTF data report import values calculated as the sum of all exports to East Germany across exporting countries. Trade values in the WTF are expressed in nominal US dollars which we translate into constant 1995 dollars using the US producer price index as reported by the OECD. Following Cameron, Proudman, and Redding (2005), we then construct a measure of the relative import intensity between West and East Germany, defined as the difference in the ratios of sector-specific imports and output.

In Section VD, we estimate the impact of industrial espionage on East German exports. For this purpose, we compute sector-specific values of exports as the sum of all imports from East Germany reported across all countries in the WTF. Since the WTF data do not include information on inner German trade flows, we also collect complementary data from the East German Statistical Yearbooks. The available information comprise export values in nominal West German deutsche mark (*Valuta-Mark*) for 86 distinct products, including exports to West Germany.

III. Case Studies

Before we introduce our empirical framework, we present two case studies that illustrate the process through which industrial espionage affected production in East Germany and how this process can be traced in the SIRA database. The first case study focuses on East Germany's microprocessor program and its heavy reliance on Western technology. The second case study zooms in on a specific niche of East Germany's chemicals sector, the production of polyester fibers and silk.

A. *Microprocessors*

At its plenary meeting in June 1977, the Central Committee of the ruling SED party highlighted the development of modern microelectronic technology as pivotal for the future of East Germany's economy. Shortly afterward the state combine

Mikroelektronik Erfurt was founded which, together with the existing combines *Robotron* and *Carl Zeiss Jena*, formed the industrial basis for East Germany's high-tech electronics program. In the race for technological leadership, the HVA provided operative support relying on a large network of informants spread across many of the West's leading microelectronics companies at the time such as DEC, IBM, Siemens, and Texas Instruments.

One of the most pressing tasks was the development of powerful microprocessors. To this end, the HVA obtained blueprints and technology of several state-of-the-art Intel and Zilog microprocessors over the second half of the 1970s, leading to the production of East Germany's first 8-bit microprocessor in 1978, the U808, an unlicensed clone of the Intel 8008. This processor was quickly superseded by the more powerful U880, a clone of the Zilog Z80, which was to become the heart of most 8-bit computers in East Germany from 1980 onward. In the transition to 16-bit microprocessors, East German electronics experts then opted for the Intel 80286 chip as the most promising archetype and, in the second half of the 1980s, the HVA delivered further prototypes of the 80386 and 80486 chips which, however, were not commercially exploited anymore.

Panel A of Figure 2 shows the number of microcomputers and office/personal computers that were produced in East Germany between 1970 and 1989.[16] Production of microcomputers took off in the late 1970s and increased steadily to about 36,000 units in 1987. Production of office and personal computers, some of which were likely referred to as microcomputers before, started in 1985 and rapidly increased to around 62,000 units in 1989. More broadly, the value of production in the product category *Machines and Equipment for Data Processing and Office Technology* more than quadrupled over the 1980s, from 1.6 billion East German mark in 1980 to 6.9 billion East German mark in 1989 (measured in constant 1985 prices). Over the same time period, exports of the two combines *Mikroelektronik Erfurt* and *Robotron*, the main producers of microprocessors and personal computers in East Germany, increased by around 121 percent.[17]

For each year between 1970 and 1989, the vertical bars in panel A of Figure 2 show the number of pieces of information recorded in SIRA that include any of the three keywords *Intel*, *Zilog*, or *Mikrorechner* (microcomputer). The first intelligence on microprocessors arrived in 1975, when the HVA received 16 pieces of information, all but one related to the chip manufacturer Intel. The first pieces of information explicitly referring to the manufacturer Zilog were recorded two years later in 1977. This staggered timing coincides with East Germany's initial focus on microprocessors from Intel before then opting for the Zilog Z80 as the basis for its own U880 chip. After a mild decline at the beginning of the 1980s, the inflow of information related to microprocessor technology increased again dramatically in 1983/1984, preceding the rapid expansion of East Germany's production of personal computers in the second half of the 1980s.

In total, based on the three keywords selected for this case study, the HVA received 2,810 distinct pieces of information related to microprocessors between 1970 and

[16] Contrary to the industry-level data used later on in our main empirical analysis, these figures are taken directly from the official statistical yearbooks of the GDR. They should therefore be viewed with a certain degree of caution.

[17] Source: archival data from the East German Statistical Office.

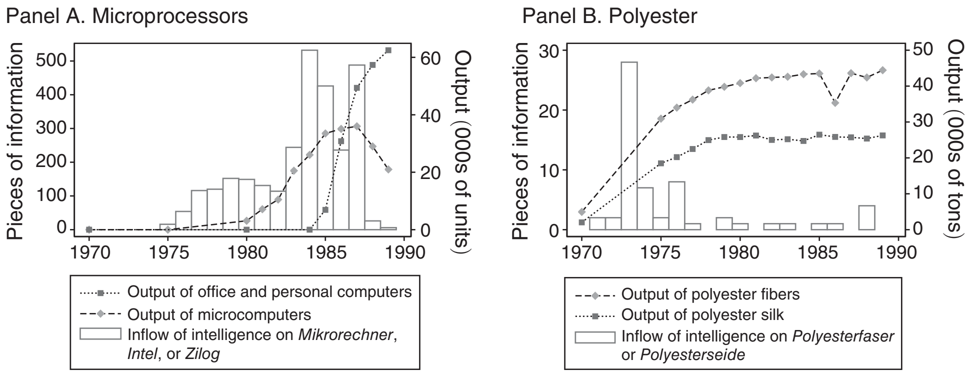

Figure 2. Case Studies

Source: SIRA subdatabase 11 for the number of pieces of information that include either of the keywords *Intel*, *Zilog*, or *Mikrorechner* (microcomputer) in panel A or *Polyesterfaser* (polyester fibers) or *Polyesterseide* (polyester silk) in panel B. For output, figures are taken from the statistical yearbooks of the German Democratic Republic. Output figures refer to the industrial production of office and personal computers (*Büro- und Personalcomputer*) and microcomputers (*Mikrorechner*) in panel A and polyester fibers (*Polyesterfaser*) and polyester silk (*Polyesterseide*) in panel B.

1989, 39 of which were given the highest quality assessment of "very valuable." Of the 219 identifiable informants who provided this information, three stand out for delivering more than 100 pieces of information each ("Dora," XV/129/78, 103 pieces; "Zentrum," XV/78/71, 113 pieces; and "Heiner," XV/456/79, 139 pieces) and one for delivering more than 1,000 pieces of information ("Seemann," XV/2768/76, 1,145 pieces, a computer specialist at DEC). While it is difficult to assess how East Germany's microelectronics sector would have evolved in the absence of the HVA's extensive espionage activities in the West, it is clear that the development would have taken place at a much slower pace. The significant technology transfer from the West appears to have played a vital role in transforming East Germany into a leader in microelectronic technology in the Eastern Bloc at the time.

B. *Polyester*

While East Germany's spying activities in the area of microprocessors can serve as a good example of how technology was acquired in the West and successfully exploited in the East, they are exceptional in terms of both their scale and the resources invested. A more typical example are the espionage activities in support of East Germany's production of polyester fibers and silk, materials widely used in the manufacturing of textiles and clothing.

Already during the construction phase of the necessary production lines, East Germany benefited from extensive information of an informant in a "leading position of western polyester production" (Eckhardt and Süß 2009). The precise way in which these complex facilities were operated turned out to be crucial for the efficiency of the production process and the quality of the final product. Luckily, an informant at the West German chemicals giant Höchst AG supplied East Germany with information about the relevant parameter settings as well as any optimization measures taken in the West to increase output in their own production facilities.

Panel B of Figure 2 shows the volume of polyester fibers and silk that were produced in East Germany between 1970 and 1989. There was a substantial increase in production of both fibers and silk, from 4,959 and 2,040 metric tonnes respectively in 1970 to 30,928 and 18,490 tonnes in 1975. This increase in output continued in the following five years but at a slower pace before eventually starting to level off after 1980 at around 42,000 and 26,000 tonnes respectively.

The vertical bars show the number of pieces of information recorded in SIRA that include either of the keywords *polyesterfaser* (polyester fiber) or *polyesterseide* (polyester silk). Accordingly, the first major inflow of information occurred in 1973 when the HVA received 28 pieces of information. These were complemented by another 17 pieces of information over the following three years. The large increase in production during the first half of the 1970s thus follows closely the major inflow of relevant intelligence. After 1976, the inflow of information on polyester ebbed away, with only 12 further pieces of information arriving until 1989.

In total, the HVA received 61 distinct pieces of information related to polyester fibers and silk between 1970 and 1989. Since regular quality assessments were only introduced in SIRA in 1980, there are only seven evaluations available, five of which received the second highest assessment of "valuable." Of the 15 identifiable informants who provided these pieces of information, the most important one was "Buerger" (XV/1931/73) who alone delivered 31 of the 61 pieces of information, most of them (20) in 1973 and the last one in 1979.

The two case studies presented illustrate how the Stasi's espionage activities in the West could directly impact the economic activity in East Germany, and how the information in the SIRA database can be exploited to establish a link between espionage activity and changes in production. Due to their specificity, they do not, however, provide a good representation of the general impact that the Stasi's industrial espionage program had on the East German economy. We therefore now turn to a more comprehensive empirical analysis that fully exploits the available information in SIRA as well as data from a wider range of industries.

IV. Empirical Framework

A. *Main Specification*

In this section, we present our empirical framework. Since conceptually, in terms of its impact on productivity growth, knowledge acquired through industrial espionage is similar to knowledge generated through R&D, we closely follow the empirical literature on R&D and productivity growth when deriving our main estimation equation. The standard approach in this literature (see, e.g., Griliches 1998 and Hall, Mairesse, and Mohnen 2010) is to specify an industry-specific Cobb-Douglas production function $Y_t = A_t K_t^{\alpha} L_t^{\beta}$, where output Y_t is produced using physical capital K_t and labor L_t, and where industry-level total factor productivity A_t is modeled as a function of an industry-specific intercept $\tilde{A}$, the R&D knowledge stock G_t, and some unobserved disturbance term $\exp(u_t)$. We extend this framework by including the stock of knowledge accruing from industrial espionage E_t as an additional driver of TFP, so that $A_t = \tilde{A} E_t^{\gamma} G_t^{\delta} \exp(u_t)$.

To focus attention on the link between industrial espionage and productivity, our estimation proceeds in two steps. We first derive measures of industry-level TFP based on the relationship $\ln A_t = \ln Y_t - \alpha \ln K_t - \beta \ln L_t$, using standard growth accounting techniques. We discuss the details of this procedure in the next subsection. In a second step, we then estimate an extended version of the log TFP equation $\ln A_t = \ln \tilde{A} + \gamma \ln E_t + \delta \ln G_t + u_t$, in which we parameterize the unobserved heterogeneity term u_t and allow for autonomous technology transfer from the frontier as an independent driver of productivity growth (similar to, e.g., Griffith, Redding, and Van Reenen 2004; Cameron, Proudman, and Redding 2005; and Buccirossi et al. 2013). Introducing country and industry subscripts, taking logarithms and differencing with respect to time, the rate of TFP growth in country i and sector j is given by

$$(1) \qquad \Delta \ln A_{ijt+1} = \gamma \Delta \ln E_{ijt+1} + \delta \Delta \ln G_{ijt+1} + \theta \ln\left(\frac{A_{jt}^F}{A_{ijt}}\right) + \lambda_{ij} + \pi_{it+1} + \mu_{jt+1} + \varepsilon_{ijt+1},$$

where $\ln(A_{jt}^F / A_{ijt})$ measures a country's distance to the world technological frontier A_{jt}^F, λ_{ij} denote country-sector fixed effects, π_{it+1} country-time fixed effects and μ_{jt+1} world-sector-time fixed effects. Since γ and δ represent the elasticities of output with respect to the knowledge stocks from industrial espionage and R&D,[18] equation (1) can be rewritten as

$$(2) \qquad \Delta \ln A_{ijt+1} = \rho\left(\frac{\Delta E_{ijt+1}}{Y_{ijt}}\right) + \eta\left(\frac{\Delta G_{ijt+1}}{Y_{ijt}}\right) + \theta \ln\left(\frac{A_{jt}^F}{A_{ijt}}\right) + \lambda_{ij} + \pi_{it+1} + \mu_{jt+1} + \varepsilon_{ijt+1},$$

where $\rho = \partial Y / \partial E$ is the marginal productivity of the espionage-based knowledge stock and $\eta = \partial Y / \partial G$ the marginal productivity of the R&D-based knowledge stock. Besides being arguably preferable from a conceptual point of view (compare Hall, Mairesse, and Mohnen 2010), the advantage of this reparameterization in terms of common marginal productivities rather than common elasticities is that changes in the espionage-based knowledge stock can now be measured by the actual inflow of information over a given time period and changes in the R&D-based knowledge stock by some proxy of R&D investments.[19] Assuming negligible rates of depreciation of both types of knowledge[20] and allowing for

[18] So $\gamma = \partial \ln Y / \partial \ln E = (\partial Y / \partial E)(E/Y)$ and $\delta = \partial \ln Y / \partial \ln G = (\partial Y / \partial G)(G/Y)$.

[19] Obtaining measures for the relative changes in the knowledge stocks $\Delta \ln E_{ijt+1}$ and $\Delta \ln G_{ijt+1}$ is not possible since the SIRA data do not include information on the initial stocks at the beginning of our sample period.

[20] In principle, the change in the knowledge stocks between any two periods would need to be adjusted for the depreciation of existing knowledge. However, it is common in the literature to assume that the corresponding depreciation rates are approximately zero (see, e.g., Griliches 1998 and Hall, Mairesse, and Mohnen 2010).

some gestation period by lagging our espionage inflow variable and R&D proxy by one period, we obtain

$$\Delta \ln A_{ijt+1} = \rho\left(\frac{S_{ijt}}{Y_{ijt}}\right) + \eta\left(\frac{R_{ijt}}{Y_{ijt}}\right) + \theta \ln\left(\frac{A^F_{jt}}{A_{ijt}}\right) + \lambda_{ij} + \pi_{it+1} + \mu_{jt+1} + \varepsilon_{ijt+1}\,, \tag{3}$$

where S_{ijt} denotes the inflow of sector-specific information acquired through industrial espionage and R_{ijt} the number of sector-specific patent applications used as a proxy for R&D investments.

Since one of the main objectives of East Germany's industrial espionage was to draw its economy technologically closer to West Germany, a natural outcome to consider is the difference in their respective TFP growth rates as represented by equation (3). Defining $\lambda_j \equiv \lambda_{Wj} - \lambda_{Ej}$, $\pi_t \equiv \pi_{Wt} - \pi_{Et}$, and $\varepsilon_{jt} \equiv \varepsilon_{Wjt} - \varepsilon_{Ejt}$, our main estimation equation is then given by

$$\Delta \ln\left(\frac{A_{Wjt+1}}{A_{Ejt+1}}\right) = -\rho\underbrace{\left(\frac{S_{Ejt}}{Y_{Ejt}}\right)}_{\text{Espionage}} + \eta\underbrace{\left(\frac{R_{Wjt}}{Y_{Wjt}} - \frac{R_{Ejt}}{Y_{Ejt}}\right)}_{\text{Patents Gap}} - \theta\underbrace{\ln\left(\frac{A_{Wjt}}{A_{Ejt}}\right)}_{\text{log TFP Gap}} + \lambda_j + \pi_{t+1} + \varepsilon_{jt+1}\,, \tag{4}$$

where we initially assume that the marginal effects of R&D intensity and the distance to the world technological frontier on TFP in West and East Germany are the same. The vector of sector-specific fixed effects λ_j in equation (4) captures differential sector-specific unobserved heterogeneity in TFP growth in West and East Germany.[21] The vector of time fixed effects π_{t+1} allows for differential technological advances on the country level that uniformly affect all sectors. By taking differences between West and East German TFP growth, we also implicitly control for all time-varying sector-specific TFP shocks μ_{jt+1} that affect both countries in the same way.[22]

The identifying assumption in estimating equation (4) is that, conditional on the included control variables, the quantity of sector-specific information delivered by East German informants is exogenous and therefore uncorrelated with the error term ε_{jt+1} $(= \varepsilon_{Wjt+1} - \varepsilon_{Ejt+1})$. There are a number of potential threats to this assumption. First, there could be a mechanical relationship between more productivity-enhancing innovations in circulation in West Germany and the amount of information East German informants are able to get their hands on. This would introduce a positive correlation between our inflow measure and ε_{Wjt+1}, which in

[21] Since the time dimension of our industry panel is relatively long, the bias of the coefficients of weakly exogenous regressors in equation (4) arising from the inclusion of country-sector fixed effects is likely to be small.

[22] Note that equation (4) does not include a term for West German industrial espionage S_{Wjt} which is unobserved and thus part of the error term. While West Germany, like most Western countries at the time, engaged in military and political espionage, we have been unable to uncover evidence of any meaningful West German industrial espionage. Assuming that the returns to industrial espionage in both countries are positive and that industry-level espionage is positively correlated across the two countries, the omission of West German espionage activities, by way of the standard omitted variable bias formula, would lead to an understatement of the effect of East German industrial espionage on the productivity gap in equation (4).

turn would lead to an upward bias of our parameter of interest toward a less negative effect. In this case, our findings would constitute a lower bound of the true effect of industrial espionage on relative productivity growth.

A second threat could arise if the East German government decided to intensify its efforts to acquire new technologies in those sectors that were expected to either fall behind or catch up with the West particularly fast. While the included relative sector-specific time trends in TFP growth λ_j pick up much of the long-run strategic direction of particular sectors, there could still be time periods in which the demand for new technologies was unusually high or low relative to the long-run trend, introducing a correlation between the error term and the inflow of information. A first step to deal with this problem is to introduce a proxy for sector-specific R&D investments, patent applications, which are likely to capture much of the variation over time in the demand for sector-specific information that may be related to relative productivity growth between West and East Germany. Furthermore, we propose two instrumental variable strategies in which we exploit the initial placement of informants on the one hand and their discontinuation as providers of information on the other hand as exogenous sources of variation.

A third threat to the exogeneity of our main regressor of interest would arise if prices for new and updated products in East Germany were systematically inflated in response to larger inflows of espionage information. While changes in the prices of existing products are fully accounted for in the sector-specific price deflators, price changes for new and upgraded products in East Germany were generally assumed to reflect real changes in their utility value and therefore not taken into consideration in the calculation of the price deflators. This could lead to an underestimation of the real price inflation if administered prices did not reflect real quality improvements and hence an overestimation of real growth. As discussed in Section IIB, in principle our industry-level data have been adjusted to account for this particular source of bias, but since it is difficult to assess the effectiveness of these adjustments, we also report results for the impact of industrial espionage on (i) a purely quantity-based measure of output, (ii) the number of new goods produced in East Germany, and (iii) the dollar value of sector-specific exports from East Germany as reported by the importing countries, all measures of output that are independent of East German price setting.

Before estimating equation (4), we need to determine the time intervals over which to construct the changes in log TFP and corresponding inflows of information and investments in R&D. Even though annual data are available, it is reasonable to consider longer first differences in the context of this study since it is unlikely that new information from the West would be fully translated into East German productivity growth within a single year. Our main specification will therefore relate changes in log TFP gaps over a 3-year period (between t and $t + 3$) to the cumulative inflow of information from industrial espionage and the number of patent applications over the previous three years (between $t - 3$ and t), both scaled by the sector-specific output in period t.

To exploit the available data as efficiently as possible and avoid arbitrariness in choosing specific start and end dates, we use overlapping observations in our main specification and cluster the standard errors to account for the mechanically introduced serial correlation across overlapping observations. We present both conventional standard errors clustered at the sectoral level and p-values calculated using the restricted wild cluster bootstrap-t procedure with Rademacher weights as proposed by Cameron, Gelbach, and Miller (2008), which can represent an important inference improvement when, as in our case, the number of clusters is relatively low (see, e.g., Djogbenou, MacKinnon, and Nielsen 2019). Note, however, that in applications in which a specific cluster is very dominant in providing the identifying variation, restricted wild cluster bootstrap tests have been shown to severely under-reject (see MacKinnon and Webb 2017). As we will see, this issue arises in some of the specifications that rely particularly strongly on variation in the electronics sector, in which case the conventional cluster-robust standard errors and the wild cluster bootstrap p-values can be viewed as providing bounds for the significance of a given estimate.

Finally, we weight observations by the average number of workers in the corresponding sector over the sample period to account for potential heterogeneity in the effect of industrial espionage on productivity. However, since weighted least squares identifies the population average partial effect only in special circumstances (see Solon, Haider, and Wooldridge 2015), we also present results in which observations are either unweighted or weighted by the average output in each sector.

B. *Measuring TFP*

Since there are no direct measures of TFP available for the time period considered, we compute these from our industry-level data using standard growth accounting techniques. As a starting point, we assume that the Cobb-Douglas production function in each sector is constant returns to scale, $Y_{ijt} = A_{ijt} K_{ijt}^{\alpha_{ij}} L_{ijt}^{1-\alpha_{ij}}$, where we allow the parameter α to differ across countries and sectors. Transforming outputs and inputs into per worker terms, taking logs and rearranging leads to

$$\ln A_{ijt} = \ln y_{ijt} - \alpha_{ij} \ln k_{ijt}, \tag{5}$$

where y_{ijt} and k_{ijt} denote output per worker and the capital-labor ratio, respectively.[23] Unfortunately, as in many industry-level datasets, there is no information on the capital stock employed in different sectors of the economy. Before we can use equation (5) to back out estimates of technological progress, we therefore have to construct measures of the sector-specific capital-labor ratios for both West and East Germany. Following the literature (e.g., Caselli 2005), we generate estimates of the capital stock in each sector using the perpetual inventory equation $K_{jt} = I_{jt} + (1 - \delta) K_{jt-1}$, where I_{jt} is investment, measured as gross fixed capital investment in constant 1995 euros, and δ the depreciation rate. In line with standard practice, we compute the initial capital stock K_{j0} using the steady-state formula $I_{j0}/(g_j + \delta)$, where I_{j0} is the value of investment in the first year available

[23] Note that one could extend the production function by allowing for differences in human capital between East and West Germany. While consistent data on the educational composition of the sector-specific workforces are not available for the time period considered, Fuchs-Schündeln and Izem (2011) shows that skills between East and West were highly transferable after unification, mitigating concerns about substantial differences in human capital in the two parts of Germany. If there were substantial differences and if these did change over time, they would be absorbed by our time fixed effects π_t as long as they are common across all sectors.

in the data (1950), and g_j the sector-specific average geometric growth rate of the investment series between 1950 and 1970, the first year with complete data on industrial espionage. As in Caselli (2005), we set the depreciation rate to 0.06 for all sectors in our baseline specification and compute the capital-labor ratio by dividing the resulting K_{jt} by the number of workers in the sector L_{jt}.

In a competitive market like West Germany, the parameters α_{ij} correspond to the sector-specific capital shares in value added. We obtain these shares directly from the EU KLEMS Growth and Productivity Accounts (November 2009 release, updated March 2011) (see O'Mahony and Timmer 2009), averaging over the period 1970 to 1989.[24] For East Germany, the situation is more complicated due to the noncompetitive environment at the time, which prevents us from using East German capital shares to calibrate the technology parameters α_{ij}. Instead, we use as proxies the aggregate sector-specific capital shares of the ten predominantly Central and Eastern European countries that joined the EU in May 2004, which are reported in the same EU KLEMS edition, averaged over the available time period 1995 to 2006.[25] For this to be a valid approach, the aggregate capital shares in these formerly communist countries need to be suitable measures of the respective technology parameters α_j, and these parameters have to be, in turn, comparable to the corresponding α_js in East Germany during the period 1970 and 1989. This would be the case if the technology parameters are time invariant and similar across countries of the former Eastern Bloc. While these assumptions are hard to verify with the available data, they seem reasonable given the similarities in economic systems and production structures between these countries during the Cold War period. In the robustness section, we will however also show results from several alternative approaches.

Having calibrated α_{ij}, we can now use equation (5) together with the observed output per worker and capital-labor ratios to back out the growth rates of TFP in West and East Germany, $\Delta \ln A_{Wjt}$ and $\Delta \ln A_{Ejt}$. Online Appendix Figure A6 displays the estimated log TFP profiles for each of our 16 sectors between 1970 and 1989. Apart from the *utilities* sector, West Germany's total factor productivity consistently outstrips East Germany's, often by a significant amount, in particular in major sectors such as *textiles and clothing*, *metalworking*, and *office appliances*, *computers*, *and electronics*. While these level differences are somewhat sensitive to the assumed sector-specific capital shares and the precise conversion of East German mark into West German Deutsche Mark (and euros) in the industry-level data, they turn out to not significantly affect the estimation of our parameter of interest. However, throughout the remainder of the paper, we also report results for the effect of industrial espionage on the log output per worker gap as an alternative measure of productivity that is directly taken from the data and does not depend on any assumptions regarding the sector-level capital shares or depreciation rates.

[24] The March 2011 update of the 2009 release of the EU KLEMS Growth and Productivity Accounts provides information on 72 distinct industries, allowing us to best match the 16 sectors available for our analysis. Since the woodworking sector has an unrealistic average labor share of more than 1, we pool it together with the paper, printing and publishing sector (as, e.g., in the EU KLEMS 2012 edition) to obtain the relevant capital share.

[25] The ten new member states are Cyprus, Czech Republic, Estonia, Hungary, Lithuania, Latvia, Malta, Poland, Slovakia, and Slovenia. For the EU10 countries, the leather sector is not separately reported in the EU KLEMS data but pooled with the textiles and clothing sector. We use the corresponding average capital share for both sectors.

Table 1—Summary Statistics

	West Germany		East Germany		Difference	
	Mean (1)	SD (2)	Mean (3)	SD (4)	Mean (5)	SD (6)
Inflow/Y			1.524	(1.403)		
Capital share	0.282	(0.152)	0.399	(0.146)		
Δlog TFP	0.028	(0.070)	0.038	(0.069)	−0.010	(0.097)
Δlog output per worker	0.050	(0.079)	0.090	(0.070)	−0.040	(0.098)
Patents/Y	0.392	(0.372)	0.313	(0.433)	0.079	(0.225)
log TFP	2.349	(0.636)	0.859	(0.605)	1.490	(0.923)
log output per worker	3.679	(0.414)	2.385	(1.091)	1.294	(0.782)
Imports/Y	2.562	(4.609)	0.312	(0.333)	2.250	(4.622)

Notes: Unweighted summary statistics computed for 3-year overlapping observations for the period 1970 to 1989 apart from the capital shares for East Germany which are based on the period 1995 to 2006 and refer to the aggregate capital shares in the ten new EU member states who joined in May 2004. Imports are cumulated over the last 3 years and measured in million dollars at constant 1995 prices. Output is measured in million euros at constant 1995 prices. Workers are measured in 1,000 so that output per worker is measured in 1,000 euros at constant 1995 prices. The number of observations 240 (234 for Imports/Y, 320 for the West German capital share, and 192 for the East German capital share).

Table 1 provides an overview of all variables used in our main empirical specification. The regressor of interest is the inflow of information scaled by sector-specific output. Over the period 1970 to 1989, the average number of pieces of information received in the last three years per million euros of output was 1.52 with a standard deviation of 1.40, reflecting substantial variation over time and sectors in the information generated by industrial espionage. The average capital share across sectors was 28.2 percent in West Germany and 39.9 percent in the ten new EU member states (whose capital shares are used as proxies for East Germany's α_{ij}). The average 3-year change in log TFP amounted to 2.8 log points in West and 3.8 log points in East Germany. Output per worker grew somewhat faster, 5.0 log points in West and 9.0 log points in East Germany.[26] The number of patent applications per 1 million euros of output was broadly comparable in West (0.392) and East Germany (0.313). As expected, the levels of log TFP and log output per worker were substantially higher in West Germany over the time period considered, with unweighted average gaps of 1.490 and 1.294 respectively. Finally, West Germany's import intensity greatly exceeded that of East Germany, by a factor of more than 8, reflecting the impact of the trade embargo imposed on the latter and its resulting difficulties in trading with the rest of the world. Online Appendix Table A4 reports corresponding statistics separately by sector and is complemented by Figures A7 and A8 which display the 3-year changes in the log TFP and output per worker gaps between West and East Germany together with the relevant inflows of information.

[26] Note that East Germany started from a much lower base in terms of TFP and output per worker in 1970 so that some convergence relative to West Germany was to be expected.

Table 2—Industrial Espionage and Productivity

	log TFP			log output per worker		
	Baseline spec (1)	Patents gap (2)	Lagged gap (3)	Baseline spec (4)	Patents gap (5)	Lagged gap (6)
Espionage	−0.034	−0.041	−0.052	−0.030	−0.040	−0.039
	(0.021)	(0.021)	(0.012)	(0.016)	(0.018)	(0.017)
Patents gap		0.071	−0.038		0.103	0.012
		(0.028)	(0.024)		(0.026)	(0.028)
log TFP gap			−0.564			
			(0.090)			
log output/worker gap						−0.514
						(0.100)
p-value WB	0.199	0.128	0.011	0.164	0.072	0.125
R^2	0.34	0.36	0.56	0.31	0.35	0.51
Observations	240	240	240	240	240	240

Notes: Sample based on 3-year intervals and overlapping observations for the period 1970 to 1989. All regressions include time- and sector-specific fixed effects. Observations are weighted by the average number of workers in a sector. The dependent variable is the change in the log TFP gap between West and East Germany over the period t to $t+3$ in columns 1 to 3 and the change in the log output per worker gap over the period t to $t+3$ in columns 4 to 6. Standard errors are clustered at the sectoral level and shown in parentheses. p-value WB denotes p-values, relating to the espionage estimate, from Cameron, Gelbach, and Miller's (2008) wild cluster bootstrap-t procedure using 999 replications.

V. Results

A. *Main Results*

OLS.—In Table 2, we present the main results of the effect of industrial espionage on the productivity gap between West and East Germany based on equation (4). Focusing on the left panel first, the most parsimonious specification that includes only our measure of sector-specific inflows of information and a full set of time- and sector-specific fixed effects reveals a negative effect of industrial espionage on the log TFP gap with a point estimate of -0.034. In column 2, we add the gap in the number of patent applications per one million euros of output as a proxy for sector-specific R&D investments. The inclusion of this control variable helps to address two potential sources of omitted variable bias. On the one hand, increased overt R&D activities in specific sectors in East Germany are likely to go hand in hand with greater efforts in acquiring corresponding information through covert operations in the West. Not controlling for East German R&D would thus lead to a downward bias in our parameter of interest toward a more negative effect. On the other hand, more R&D activities in West Germany could mean that there is more information around that could be siphoned off by East German informants. In this case, not controlling for West German R&D would give rise to an upward bias in our parameter of interest. As column 2 reveals, the latter effect dominates: controlling for the patents gap between West and East Germany reduces the estimate to a more negative -0.041. Column 3 represents our preferred specification, where we add the initial log TFP gap as an additional control variable to allow for autonomous technology transfers. This leads to a further decrease of our main parameter of interest to -0.052, which is significant based on both the conventional cluster-robust standard

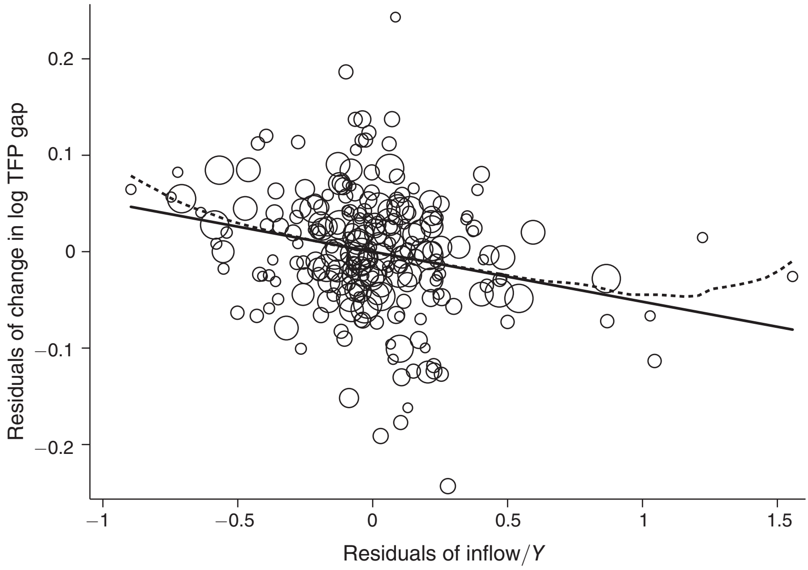

Figure 3. Industrial Espionage and Productivity

Notes: The figure plots residualized changes in the log TFP gap between West and East Germany against residualized sector-specific inflows of information on the basis of the specification reported in column 3 of Table 2. Circles are proportional to the square root of the average number of workers in an industry. The solid black line represents the OLS regression line and the dashed line the fit from a local polynomial regression.

errors reported in parentheses and the p-value from Cameron, Gelbach, and Miller's (2008) wild cluster bootstrap-t procedure shown at the bottom of the table.

The estimated coefficient of -0.052 suggests an economically meaningful effect of industrial espionage on relative productivity growth, with a one standard deviation increase of 1.40 in the information flow per one million euros of output reducing the log TFP gap between West and East Germany by 7.3 percentage points (or 4.9 percent relative to the average gap of 1.49, see Table 1). In Section VG, we provide further evidence on the implied magnitude of this effect by simulating the evolution of the TFP gap between West and East Germany in the absence of industrial espionage. Note that the coefficient of the initial log TFP gap, multiplied by –1, measures the marginal effect θ of the distance to the world technological frontier on TFP growth (compare equation (1)). In line with much of the existing literature, we find evidence for independent technology transfer as a source of productivity growth for countries behind the technological frontier.

Figure 3 visualizes the negative relationship between industrial espionage and changes in the log TFP gap between West and East Germany by plotting their residualized values based on our preferred specification in column 3 of Table 2. Importantly, this relationship is not driven by any outliers and, over much of the inflow variable's support, well approximated by a linear function.

The right panel of Table 2 reports the corresponding results for the change in the log output per worker gap which closely mirror those for the log TFP gap. Online Appendix Table A5 shows results for the same set of specifications but based on non-overlapping observations for the years 1973, 1976, 1979, 1982, and 1985.

While less precisely estimated due to the smaller sample size, all estimates remain similar in magnitude to their counterparts in Table 2.

Instrumental Variables.—One potential concern regarding the OLS results is that they might be confounded by time-varying unobservable factors that jointly affect the extent of industrial espionage and the speed at which the productivity gaps between West and East Germany change in particular industries. One such source of endogeneity could be a mechanical one in which the presence of more innovations in the West widens the productivity gap to the East while at the same time increasing the inflow of espionage information even in the absence of any systematic change in behavior on the part of the Stasi's informants. This is because, at constant espionage intensity, when there is more information on new innovations around, it is easier for informants to appropriate some of this information and relay it back to the Stasi. In this case, the inflow measure would be positively correlated with the error term ε_{Wjt+1} in equation (4), attenuating our estimate of the impact of industrial espionage on the productivity gap between West and East Germany. Besides this mechanical source of endogeneity, it is possible that East Germany strategically intensified its espionage activities in precisely those sectors in which it correctly anticipated to either catch up with the West (in which case our parameter of interest would overstate the impact of industrial espionage on relative productivity growth) or technologically fall behind in the future (in which case our estimates would understate the relevant impact).

By exploiting variation around sector-specific linear time trends in relative productivity growth, which are absorbed by the vector of λ_js, and additionally controlling directly for the initial gap in TFP as well as the gap in the number of patent applications as a proxy for R&D investments, we already expect to capture much of the East German government's changing preferences for certain sectors over time. To address any remaining concerns, we implement two instrumental variable approaches, both exploiting the fact that the Stasi's main way of strategically changing the volume and sectoral distribution of espionage information was through a differential allocation of new informants across sectors.[27]

In the first approach, we assume that the presence of "old" informants, defined as informants who were already active at the beginning of the sample period in 1970, and their differential access to information across sectors at that time are exogenous to any subsequent changes in the preferences of the Stasi. More specifically, we instrument the inflow of information received between the end of period $t-3$ and period t with the inflow of information received from informants who already provided information at the beginning of the sample period in 1970, holding their sectoral distribution constant. Let $\theta_{i,70}$ be the share of the total information received in 1970 that was sent by informant i, and let $\lambda_{ij,70}$ be the fraction of that information pertaining to sector j. In the spirit of a classical shift-share analysis, the numerator of the instrument is then constructed as $\sum_{i\in 1970}\theta_{i,70}\lambda_{ij,70}\sum_{s=t-2}^{t}I_s$, where I_s is the total inflow in year s received from sources who were already active in 1970. In the absence of any sector-specific demand shocks for information, one would expect

[27] The reshuffling of existing informants across sectors was difficult since most of them had specific technical training and were gathering information under the cover of a long-term career in specifically targeted Western companies.

Table 3—Instrumental Variables

	log TFP				log output per worker			
	Old informants		Exit of informants		Old informants		Exit of informants	
	First stage (1)	IV results (2)	First stage (3)	IV results (4)	First stage (5)	IV results (6)	First stage (7)	IV results (8)
Espionage		−0.072 (0.024)		−0.120 (0.036)		−0.059 (0.028)		−0.119 (0.040)
Patents gap	−0.569 (0.392)	−0.034 (0.024)	−0.014 (0.232)	−0.059 (0.048)	−0.528 (0.387)	0.018 (0.025)	0.017 (0.196)	0.001 (0.049)
log TFP gap	0.009 (0.446)	−0.571 (0.094)	0.544 (0.566)	−0.679 (0.140)				
log output/ worker gap					0.299 (0.305)	−0.514 (0.096)	0.844 (0.383)	−0.613 (0.133)
Instrument old informants	0.631 (0.081)				0.639 (0.082)			
Instrument exits			−4.395 (0.619)				−4.568 (0.536)	
p-value WB		0.150		0.149		0.353		0.188
F-statistic	61.4		50.4		60.5		72.6	
Observations	240	240	192	192	240	240	192	192

Notes: Sample based on 3-year intervals and overlapping observations for the period 1970 to 1989. All regressions include time- and sector-specific fixed effects. Observations are weighted by the average number of workers in a sector. The dependent variable is the change in the log TFP gap between West and East Germany over the period t to $t+3$ in columns 1 to 4 and the change in the log output per worker gap over the period t to $t+3$ in columns 5 to 8. In columns 1, 2, 5, and 6, the instrument is constructed as $(\sum_{i \in 1970} \theta_{i,70} \lambda_{ij,70} \sum_{s=t-2}^{t} I_s)/Y_{jt}^E$, where $\theta_{i,70}$ is the share of the total information received in 1970 sent by informant i, $\lambda_{ij,70}$ is the fraction of that information pertaining to sector j, and I_s is the total inflow in period s received from sources already active in 1970. In columns 3, 4, 7, and 8, the instrument is constructed as $(\sum_{s=t-5}^{t-3} \sum_{i^*(s)|\bar{I}_{i^*j} \geq 20} \bar{I}_{i^*j})/Y_{jt}^E$, where $\bar{I}_{i^*j}$ is the average annual inflow of information generated by informant i^* pertaining to sector j over the entire sample period, and $i^*(s)$ denotes all informants who are last observed in period s. Standard errors are clustered at the sectoral level and shown in parentheses. p-value WB denotes p-values, relating to the espionage estimate, from Cameron, Gelbach, and Miller's (2008) wild cluster bootstrap-t procedure using 999 replications.

this inflow to be related to different industries according to the initial placement of the original sources across these industries (as captured by $\lambda_{ij,70}$) and their relative effectiveness in generating information (as captured by $\theta_{i,70}$).

Columns 1 and 5 of Table 3 show the first-stage results for the change in the log TFP and output per worker gap, respectively. The predicted inflow of information, constructed under the assumption of constant relative productivities and sectoral distributions of the old informants, is a strong predictor of the actual information inflows, with F-statistics of 61.4 and 60.5, respectively. As reported in columns 2 and 6, the second-stage IV estimates are somewhat more negative than our baseline OLS estimates, which could indicate some degree of endogeneity, either because of the mechanical relationship described above or because espionage activities tended to be intensified in those sectors in which East Germany was correctly anticipated to fall behind.

In our second IV approach, we exploit the fact that several informants who previously used to provide a steady stream of information at some point abruptly cease to deliver any further information. This could happen because these informants fell ill, lost or retired from their jobs, or because they were uncovered or at danger of being uncovered, in which case the Stasi would either deactivate or try to repatriate them before they could be apprehended. While we do not know the specific reasons for why individual sources discontinued their work for the Stasi, it is likely that in many cases these reasons were orthogonal to the Stasi's own strategic objectives. We operationalize this intuition by instrumenting the inflow of information received between the end of period $t-3$ and period t with the hypothetical inflow that would have been expected to arrive at the Stasi from exiting informants had these continued to provide information at the same rate as before. More specifically, the numerator of the instrument is constructed as $\sum_{s=t-5}^{t-3} \sum_{i^*(s)|\bar{I}_{i^*j} \geq 20} \bar{I}_{i^*j}$ where $\bar{I}_{i^*j}$ is the average annual inflow of information generated by informant i^* pertaining to sector j over the entire sample period, and $i^*(s)$ denotes the set of all informants who were last observed in the data in period s (compare the right panel of online Appendix Figure A3). The more informants exit during a given period and the more prolific they were in the past in generating information, the more their loss will be felt in the future in the form of lower volumes of information inflows. Since the Stasi may have endogenously deactivated informants in slow-moving sectors, we only include very productive informants, those who previously generated more than 20 pieces of information per year, when constructing the instrument as their permanent exits are particularly likely to be exogenous.[28]

The identifying assumption for this approach to be valid is that our exit-based instrument is uncorrelated with the error term ε_{jt+1} $(= \varepsilon_{Wjt+1} - \varepsilon_{Ejt+1})$ in equation (4). Since most of the possible reasons for the sudden exit of a highly prolific informant were outside the control of the Stasi, we argue that our exit-based instrument is unlikely to be endogenous with respect to East German productivity growth (ε_{Ejt+1}). Even if it were endogenous, the type of correlation that would bias our IV results toward a more negative effect and thus lead to an overstatement of the impact of industrial espionage on productivity growth would require exits of prolific informants in West Germany to be more prevalent in those sectors in which East Germany is growing more slowly (ε_{Ejt+1} is smaller). This seems to be the less likely scenario since the Stasi would arguably have a particular interest in maintaining informants in precisely those sectors.

The observation that the observed exits are beyond the Stasi's control does not necessarily mean that they are also exogenous with respect to West German productivity growth $\left(\varepsilon_{Wjt+1}\right)$. In particular, an informant's retirement or job loss could indicate that the West German sector in which he/she operates is doing badly, potentially generating a negative correlation between the exit-based instrument and the error term ε_{Wjt+1}. In this case our IV estimate would be biased upward toward a less negative effect and thus understate the true impact of industrial espionage on productivity growth. Another concern could be that West Germany might have intensified its counterintelligence activities, and thus triggered a higher exit rate of informants, in precisely those sectors in which it was about to make substantial technological progress. Contrary to the previous case, the bias would then lead us to overstate the impact of industrial espionage on productivity growth. There is no historical evidence that would point toward such systematic counterintelligence responses on the sectoral level by West German authorities. Considering the extent

[28] As a robustness check, we use alternative thresholds of 10 and 50 pieces of information as well as a simple count of the number of exits of prolific informants as an instrument, leading to very similar results.

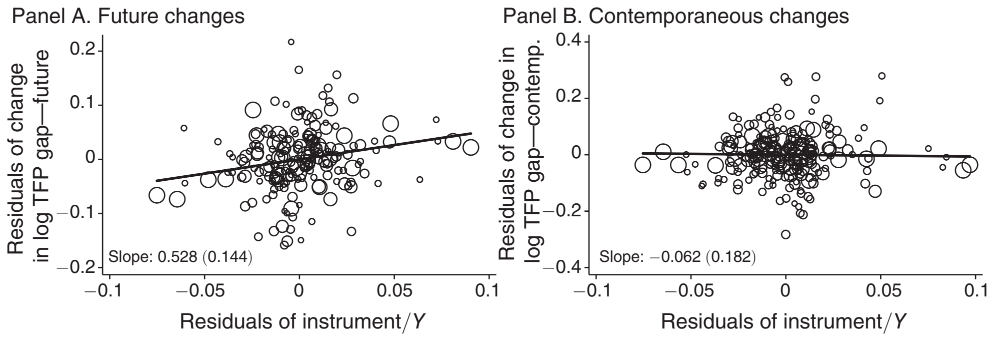

FIGURE 4. EXITS OF INFORMANTS AND CHANGES IN THE LOG TFP GAP

Notes: The figure plots residualized changes in the log TFP gap between West and East Germany against residualized exits of highly prolific informants scaled by output. Exits are measured between the end of period $t - 6$ and $t - 3$. Changes in the log TFP gap are measured between the end of period t and $t + 3$ in panel A and the end of $t - 6$ and $t - 3$ in panel B. Circles are proportional to the square root of the average number of workers in an industry. The solid black lines represent the OLS regression lines.

of East Germany's infiltration of the West German economy, the actual exposure of informants engaged in industrial espionage was very limited, so that the vast majority of observed exits of highly prolific informants were arguably driven by other unrelated factors.

Figure 4 provides suggestive evidence for the absence of a relationship between exits of productive informants and the contemporaneous performance of a sector. In panel A, we show the reduced-form relationship between our (residualized) exit-based instrument and future changes in the log TFP gap between West and East Germany.[29] The relationship is positive with a significant point estimate of 0.528, indicating that more exits of prolific informants in the past (measured between the end of period $t - 6$ and $t - 3$) lead to a widening of the log TFP gap between West and East Germany in the future (measured between t and $t + 3$). In panel B, we use the same specification but now depict the relationship between the instrument and contemporaneous changes in the log TFP gap (so also measured between $t - 6$ and $t - 3$). The small and insignificant point estimate of -0.062 shows that the exits of productive informants are unrelated to contemporaneous relative TFP growth, suggesting that they were not the result of a strategic counterintelligence response of the West or a systematic exiting or deactivation of informants in slow-moving sectors.

Columns 3 and 7 of Table 3 report the first-stage results corresponding to the reduced-form relationships illustrated in the left panels of Figure 4 and online Appendix Figure A9, respectively. The exit of informants has, as expected, a negative effect on the future inflow of information. The associated second-stage estimates shown in columns 4 and 8 are substantially larger than our baseline OLS estimates, by a factor of more than 2, which would be consistent with an endogenous intensification of industrial espionage in sectors in which the productivity gap to West Germany was widening but also with heterogeneous treatment effects

[29] Online Appendix Figure A9 shows the corresponding evidence for the log output per worker gap.

across different sectors and types of information. While old informants are quite similar to the typical informant in the sample, both in terms of their sectoral distribution and the type of information they deliver, the group of informants underlying our exit-based instrument is much more concentrated in the electronics sector and delivers not only more but also qualitatively better information.[30] In conjunction with our findings in Section VE, where we show that high-quality pieces of information have by far the biggest impact on East German productivity growth, this is likely to explain much of the greater magnitude of our exit-based IV estimates.

B. *Decompositions*

While our results so far show robust evidence that industrial espionage had a diminishing effect on the productivity gap between West and East Germany, the implicit assumption in interpreting this finding has been that this reduction is driven by a positive effect on East German productivity growth. In the first three columns of Table 4, we explicitly test for the appropriateness of this interpretation by studying separately the effects on the two countries' individual TFP growth rates. Because of the relatively strict separation of markets in which West and East German firms operated during the Cold War, one would expect industrial espionage to have an impact on East German productivity growth but little to no impact on West German productivity growth.[31] Our empirical results strongly support this intuition, showing a positive and significant effect on East German TFP growth and a relatively small and only marginally significant effect on West German TFP growth. Only the exit-based IV results indicate a more substantial negative effect on West German TFP growth, likely reflecting the particularly high value of the information provided by exiting informants. Note that separately considering the impact of industrial espionage on West and East German TFP growth comes at a price since, without differencing between the two countries, any unobserved world-sector-time fixed effects μ_{jt} remain in the error term (compare equation (3)).

The decompositions in columns 1 to 3 of Table 4 are useful in assessing the relative contribution of West and East German productivity growth to our main findings since, by construction, the resulting estimates sum up to those presented in Tables 2 and 3. However, the estimated specifications are not fully consistent with the empirical framework set out in Section IV. In columns 4 to 6, we therefore report the results from an alternative set of specifications that are more closely related to our country-specific TFP growth equation (3). In column 4, we allow West and East German patent intensities to appear separately in the regression, essentially relaxing the restriction on the equality of the parameter η in both countries. This

[30] Of the 147 exiting informants, 78.2 percent delivered primarily information related to the *Office Appliances, Computers, and Electronics* sector, compared to only 49.8 percent in the overall sample and 50.0 percent in the sample of 304 old informants. On a scale from 1 ("very valuable") to 5 ("no value"), the average quality delivered by exiting informants is 2.73, compared to 2.85 in the overall sample and 2.87 in the sample of old informants. At the top end of the quality distribution, the fraction of information receiving the highest possible assessment is 2.8 percent among exiting informants but only 1.9 percent in the overall sample and 1.6 percent among old informants.

[31] This prediction would change if both countries operated in an integrated and internationally competitive market where industrial espionage may lower productivity growth in the targeted country by increasing product market competition from the perpetrating country.

Table 4—Decompositions

	Baseline decomposition			Flexible decomposition		
	FRG/GDR (1)	FRG (2)	GDR (3)	FRG/GDR (4)	FRG (5)	GDR (6)
OLS						
Espionage	−0.052	−0.009	0.043	−0.036	−0.010	0.046
	(0.012)	(0.005)	(0.012)	(0.009)	(0.005)	(0.012)
Patents gap	−0.038	0.004	0.043			
	(0.024)	(0.019)	(0.020)			
log TFP gap	−0.564	−0.208	0.356	−0.594		0.319
	(0.090)	(0.069)	(0.058)	(0.088)		(0.051)
GDR patents/Y				−0.083		−0.022
				(0.057)		(0.038)
FRG patents/Y				−0.147	0.073	
				(0.069)	(0.028)	
p-value WB	0.011	0.109	0.011	0.000	0.035	0.001
R^2	0.56	0.66	0.45	0.57	0.61	0.44
Observations	240	240	240	240	240	240
IV: Old informants						
Espionage	−0.072	−0.025	0.047	−0.023	−0.031	0.068
	(0.024)	(0.018)	(0.014)	(0.038)	(0.017)	(0.016)
Patents gap	−0.034	0.007	0.042			
	(0.024)	(0.020)	(0.018)			
log TFP gap	−0.571	−0.214	0.357	−0.594		0.335
	(0.094)	(0.067)	(0.055)	(0.074)		(0.057)
GDR patents/Y				−0.099		−0.032
				(0.079)		(0.047)
FRG patents/Y				−0.164	0.091	
				(0.083)	(0.039)	
p-value WB	0.150	0.332	0.030	0.565	0.135	0.036
F-statistic	61.7	61.7	61.7	14.1	14.1	52.5
Observations	240	240	240	240	240	240
IV: Exit of informants						
Espionage	−0.120	−0.035	0.085	−0.090	−0.024	0.090
	(0.036)	(0.017)	(0.028)	(0.038)	(0.017)	(0.034)
Patents gap	−0.059	−0.005	0.054			
	(0.048)	(0.029)	(0.034)			
log TFP gap	−0.679	−0.278	0.402	−0.706		0.368
	(0.140)	(0.102)	(0.090)	(0.127)		(0.081)
GDR patents/Y				−0.029		−0.059
				(0.088)		(0.064)
FRG patents/Y				−0.156	0.094	
				(0.118)	(0.050)	
p-value WB	0.149	0.143	0.320	0.109	0.236	0.362
F-statistic	50.4	50.4	50.4	35.3	70.8	31.2
Observations	192	192	192	192	192	192

Notes: Sample based on 3-year intervals and overlapping observations for the period 1970 to 1989. All regressions include time- and sector-specific fixed effects. Observations are weighted by the average number of workers in a sector. The dependent variable is the change in the log TFP gap between West and East Germany over the period t and $t + 3$ in columns 1 and 4 and the change in log TFP between t and $t + 3$ in West and East Germany in columns 2 and 5 and 3 and 6, respectively. The instrumental variables are described in Section VA. Standard errors are clustered at the sectoral level and shown in parentheses. p-value WB denotes p-values, relating to the espionage estimate, from Cameron, Gelbach, and Miller's (2008) wild cluster bootstrap-t procedure using 999 replications.

has qualitatively little bearing on our main findings. Quantitatively, the higher flexibility of the specification leads to an around one-third smaller estimated effect of the impact of industrial espionage on changes in the log TFP gap.[32] In columns 5 and 6, we then estimate equation (3) separately for West and East Germany, assuming that West Germany constituted the world technological frontier throughout the time period considered (so that $A_{Wjt} = A_{jt}^{F}$). The results closely echo those of the baseline decomposition, with industrial espionage closing the West-to-East productivity gap by primarily accelerating East German TFP growth. Online Appendix Table A6 reports the corresponding results for output per worker.

C. *Robustness Checks*

Main Specification.—In Table 5, we perform a number of robustness checks for our main OLS and IV results, which are restated for comparison in column 1. We focus on the impact of industrial espionage on the log TFP gap but report the results for output per worker in online Appendix Table A7. In column 2, we weight each observation with the average value of output in each sector over the sample period rather than the average number of workers. This increases both the OLS and IV estimates by around one-half. In contrast, not weighting at all reduces the estimated effects mildly as shown in column 3. In column 4, we exclude all observations pertaining to the sector *Office Appliances*, *Computers, and Electronics*, which comprises by far the biggest share of the overall information received (compare Figure 1). Excluding this important sector has little impact on the estimated coefficients. Only the IV estimate based on old informants now becomes statistically insignificant. In column 5, we add sector-specific linear time trends to our specification, effectively allowing for accelerating or decelerating relative productivity growth in different sectors. While this has little effect on the OLS estimate, it reduces the IV estimate based on old informants to an insignificant -0.009 and increases the exit-based IV estimate to a quantitatively large value of -0.213. In column 6, to account for the impact of international trade on productivity growth, we add the gap in sector-specific import intensities between West and East Germany as an additional control variable which once again leaves the coefficients almost unchanged.

In the last two columns, we check the robustness of our results to alternative ways in which to allocate pieces of information to different sectors. In column 7, we assign each piece of information to the relevant sectors in proportion to the number of sector-specific keywords describing it. For example, if a piece of information is described by the keywords "Optoelectronics," "Microelectronics," and "Chemistry," we count it as a $2/3$ information for the *Office Appliances*, *Computers, and Electronics* sector and a $1/3$ information for the *Chemicals* sector. Using this weighted measure of information inflows increases the estimated impacts substantially, both in the OLS and in the IV estimations. Our results based on the unweighted inflow measure might thus be interpreted as a lower bound. Apart from the weighting issue, another potential problem of mapping pieces of information to different sectors on the basis of the 2,000 most frequently occurring keywords is that

[32] Including West and East German log TFP separately as control variables leaves the point estimate on the industrial espionage regressor virtually unchanged at -0.036 (0.010).

Table 5—Robustness: log TFP

	Main spec (1)	Weighted by output (2)	No weights (3)	No IT (4)	Sector trends (5)	Trade gap (6)	Keyword weighted (7)	Machine learning (8)
OLS								
Espionage	−0.052	−0.077	−0.047	−0.047	−0.044	−0.053	−0.090	−0.049
	(0.012)	(0.032)	(0.013)	(0.016)	(0.012)	(0.012)	(0.024)	(0.017)
p-value WB	0.011	0.080	0.028	0.027	0.034	0.008	0.056	0.436
R^2	0.56	0.59	0.54	0.54	0.72	0.57	0.56	0.55
Observations	240	240	240	225	240	234	240	240
IV: Old informants								
Espionage	−0.072	−0.116	−0.070	−0.050	−0.009	−0.077	−0.112	−0.081
	(0.024)	(0.048)	(0.028)	(0.042)	(0.039)	(0.027)	(0.039)	(0.030)
p-value WB	0.150	0.188	0.070	0.296	0.841	0.174	0.192	0.241
F-statistic	61.4	59.5	23.9	37.8	16.8	57.1	24.2	18.6
Observations	240	240	240	225	240	234	240	240
IV: Exit of informants								
Espionage	−0.120	−0.168	−0.109	−0.144	−0.213	−0.117	−0.275	−0.118
	(0.036)	(0.072)	(0.040)	(0.078)	(0.068)	(0.035)	(0.086)	(0.031)
p-value WB	0.149	0.241	0.041	0.036	0.006	0.163	0.150	0.087
F-statistic	50.4	53.7	23.3	3.8	11.5	47.1	27.5	27.9
Observations	192	192	192	180	192	189	192	192

Notes: Sample based on 3-year intervals and overlapping observations for the period 1970 to 1989. All regressions include time- and sector-specific fixed effects, the patents gap, and the initial log TFP gap as additional regressors. Observations are weighted by the average number of workers in a sector (apart from columns 2 and 3). The dependent variable is the change in the log TFP gap between West and East Germany over the period t to $t + 3$. Column 1 restates our main results from column 3 of Table 2. In column 2, observations are weighted by the average sector-specific gross value added. In column 3, observations are unweighted. In column 4, we exclude the IT sector from the estimation sample. In column 5, we include sector-specific linear time trends in the specification. In column 6, we include the gap in the sector-specific import/output ratio between West and East Germany as an additional control variable. In column 7, we weight each piece of information according to the number of categorized keywords assigned to each sector. In column 8, we use machine learning methods to assign pieces of information to industry sectors. Standard errors are clustered at the sectoral level and shown in parentheses. p-value WB denotes p-values, relating to the espionage estimate, from Cameron, Gelbach, and Miller's (2008) wild cluster bootstrap-t procedure using 999 replications.

a nonnegligible fraction of 18.6 percent of the total information received cannot be assigned to a sector since they are not described by any of the allocated keywords (see Section IIA). Furthermore, by focusing on a limited set of frequently occurring keywords, we might ignore valuable information embedded in the remaining less frequently occurring keywords. To address this issue, we use machine learning tools to systematically assign pieces of information to individual sectors on the basis of the universe of keywords recorded in the data.[33] As shown in column 8, this

[33] We proceed as follows: we first create a training dataset consisting of 1,000 randomly selected pieces of information which we manually assign to either one of the 16 sectors included in our analysis or, if not applicable, to a residual sector. We then train a linear support vector machine classifier on the training data (see Cortes and Vapnik 1995) using the *scikit-learn* open-source library for Python. In our context, the set of unique keywords, appropriately preprocessed by stemming and the removal of unnecessary punctuation, constitutes the feature space based on which the classification takes place. When applied to the unlabeled data, the trained classifier calculates for each piece of information individual scores over the different sectors. For a given piece of information, the sector with the highest score is then chosen as the sector to which the information pertains. After training the algorithm on the entire training data, we obtain an in-sample prediction accuracy of 98.4 percent. To test the performance of the algorithm on the unlabeled dataset, we train the algorithm on 80 percent of the labeled observations and test its performance on the remaining 20 percent, achieving an accuracy in this hold-out exercise of 71 percent.

more sophisticated approach yields similar point estimates as our initial approach. However, since the ability of the machine learning approach to make correct out-of-sample predictions is relatively poor, most likely owing to the fact that there are often only a few keywords available to describe a given piece of information and that many of these keywords occur very infrequently in the data, we decided to focus on the more direct approach based on allocated keywords when presenting our results.[34] Online Appendix Table A7 reports the corresponding results for output per worker.

One concern regarding the main estimation equation (4), already alluded to by Griliches (1998), is the presence of sector-specific output Y_{Ejt} in the denominators of both the regressor of interest and the dependent variable.[35] This could introduce a spurious positive correlation between our espionage inflow measure and TFP growth in East Germany, for instance because of measurement error in current output, biasing the main estimates downward toward a more negative effect. To assess the importance of this issue, we conduct a placebo test in which we randomly reshuffle the 240 observed espionage inflows S_{Ejt} (the numerator of our regressor of interest) across observations defined by sector and year. We then construct hypothetical inflow rates by dividing these placebo inflows by the actual sector-specific outputs Y_{Ejt} and reestimate our model using the same set of control variables as in our baseline specifications in columns 3 and 6 of Table 2. Figure 5 shows the resulting distributions of estimated coefficients from 1,000 random reshuffles. For both outcome variables, these distributions are closely centered around zero, with a mean of 0.0002 and 0.0001, a standard deviation of 0.0013 and 0.0013, and a range between -0.0049 and 0.0066 and -0.0054 and 0.0052, respectively. The absence of any systematic relationship in these placebo estimations suggests that our OLS estimates of -0.052 and -0.039 are not driven by a mechanical relationship between the regressor of interest and the dependent variable.

In the online Appendix, we provide a number of further robustness checks. In Tables A8 and A9, we vary the length of the time interval over which we compute productivity growth and the lagged inflow of information. As expected, due to the shorter time horizon to translate new information into technological progress, the effect of industrial espionage on the productivity gap between West and East Germany is muted when estimated from annual variation, both in the OLS and the IV models based on old informants. The counterintuitive positive estimates in most of the exit-based IV regressions in turn point toward a possible violation of the exclusion restriction. Despite their negative impact on the inflow of information in the following year (the first stage), more exits of highly prolific informants have, contrary to the baseline case, a negative effect on the future change in the log productivity gap (the reduced-form results). The likely reason is that the number of

[34] The unusually large wild cluster bootstrap p-values in column 8, particularly for the OLS results, appear to be due to the machine learning approach assigning the vast majority of pieces of information to the electronics sector (since only the sector with the highest score is chosen as the sector to which a given piece of information is assigned). As shown by MacKinnon and Webb (2017), when the number of treated clusters is very small, restricted wild cluster bootstrap tests are likely to result in severe under-rejection. Indeed, plotting the distribution of the bootstrap t-statistics underlying the p-values in column 8 reveals a highly bimodal distribution (see the left panel of online Appendix Figure A10), indicating that the restricted wild cluster bootstrap-t procedure is unlikely to provide valid inference in these cases.

[35] Note that $\Delta \ln A_{Ejt+1} = \ln(Y_{Ejt+1}/Y_{Ejt}) - \alpha_{ij} \ln(K_{Ejt+1}/K_{Ejt}) - (1 - \alpha_{ij}) \ln(L_{Ejt+1}/L_{Ejt})$.

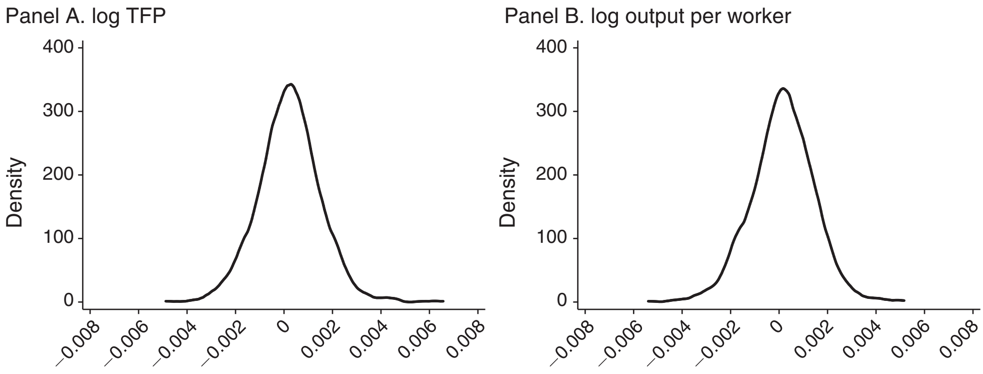

Figure 5. Placebo Tests

Notes: The figure shows the distribution of 1,000 estimated coefficients representing the impact of hypothetical espionage inflow rates on changes in the log TFP gap (panel A) and log output per worker gap (panel B) between West and East Germany. Each estimate is obtained by (i) randomly reshuffling the 240 actual espionage inflows S_{Ejt} across observations defined by sector and year, (ii) computing hypothetical espionage inflow rates by dividing the randomly assigned inflows by the actual sector-specific outputs Y_{Ejt}, and (iii) estimating the model by OLS using the same set of control variables as in the main specifications reported in columns 3 and 6 of Table 2. The plotted densities are based on an Epanechnikov kernel function with default bandwidth 0.0003.

exits indirectly proxies for the amount of information received in the past and that, at this short time horizon, this information is still in the process of being translated into East German productivity growth. When we use five-year intervals, the point estimates (apart from the exit-based IV results) are broadly similar to our main estimates but often not statistically significant due to the smaller sample size and the more limited variation in these estimations.

Online Appendix Tables A10 and A11 report results for different functional forms of our espionage inflow measure. In columns 1 to 3, we lag the denominator by one period, thus defining the inflow measure as S_{Ejt}/Y_{Ejt-3}. In columns 4 to 6, we normalize by the value of sector-specific output at the beginning of the sample period in 1970, and in columns 7 to 9 by the average value of sector-specific output over the entire sample period. While the resulting OLS estimates are smaller in magnitude than our baseline results, especially when normalizing with initial output, they remain statistically significant in the preferred specification that also controls for the initial productivity gap as an independent driver of productivity growth.[36] The corresponding IV estimates, while almost always carrying a negative sign, are more noisy and in many cases not statistically significant, especially when normalizing by initial and average output.[37] This loss in precision is due to a significant weakening of the first-stage relationships between the instruments and the espionage inflow

[36] Even in the absence of any spurious correlation between regressor and dependent variable, one would expect these alternative normalization to generate smaller estimates since output has been growing over the sample period so that dividing by its lagged value leads to higher values of the regressor and thus smaller point estimates. Over the sample period, the average 3-year growth rate of sector-specific output in East Germany was 10.4 percent, so that the inflow measures normalized by output in $t-3$ are on average scaled up by a factor of 1.104 relative to the corresponding measures normalized by output in period t.

[37] Once again, the unusually large wild cluster bootstrap p-values for the exit-based IV estimates in online Appendix Tables A10 and A11 are unlikely to provide valid inference since almost all the variation exploited through this instrument arises from exits of informants in the electronics sector, generating a highly bimodal

measure, making it difficult to draw strong conclusions from the resulting estimates. In the remaining columns of online Appendix Tables A10 and A11, we report results for functional forms that do not involve an output-based normalization. In columns 10 to 12, we normalize by sectoral employment. In columns 13 to 15, we regress directly on the number of pieces of information without any scaling, and in columns 16 to 18 on the log number of pieces of information. Most of the resulting estimates have the expected negative sign but are not statistically significant. While these specifications have no theoretical foundation (compare Section IV), this weakening of the empirical findings indicates some sensitivity to alternative functional form assumptions.

TFP Calculation.—As discussed in Section IVB, the construction of sector-specific TFP measures is complicated by the noncompetitive environment in East Germany at the time, which prevents us from following the standard approach of proxying the technology parameters α_{ij} by sector-specific capital shares in value added. In online Appendix Tables A12, A13, and A14, we show that our main OLS and IV results are robust to different calibrations of α_{ij} and different assumptions about the depreciation rates used in the computation of sector-specific capital stocks. One obvious alternative to our preferred approach of using capital shares in the new Central and Eastern European EU member states as proxies for the α_js in East Germany would be to assume that these technology parameters were comparable across West and East German industries during the 1970s and 1980s and then use West German sector-specific capital shares for both countries. Column 2 in the top panel of each table shows that this alternative approach leads to similar results as our preferred approach (restated in column 1 for comparison). The same holds if we make the simple assumption of a common value for α of 0.2, 0.33, or 0.4 across all sectors in both countries (columns 3 to 5).

Apart from the parameters α_{ij}, another calibrated parameter is the depreciation rate of the capital stock δ. In our baseline specification, we set this rate to 6 percent for all sectors, a value regularly chosen in the literature in the absence of more concrete evidence. The middle panels of online Appendix Tables A12, A13, and A14 show that our main estimates are stable over a wide range of alternative depreciation rates. In the bottom panel, we allow the depreciation rate to differ between West and East Germany, which could be due to a different mix of asset types such as structures, machinery, or transport equipment in both countries. For West Germany, we take the average of the annual depreciation rates of the capital stock reported in the Penn World Table 9.0 (see Feenstra, Inklaar, and Timmer 2015) for the period 1970 to 1989 (4.2 percent). For East Germany, direct information is not available, so we use the unweighted average of all reported depreciation rates pertaining to Central and Eastern European countries, once again averaging them over the period 1970 to 1989 (5.1 percent).[38] The resulting estimates are virtually identical to those in our baseline specification. Overall, these findings show that different assumptions about

distribution of bootstrap *t*-statistics that leads to a severe under-rejection of the tested null hypothesis (see the right panel of online Appendix Figure A10 as an example).

[38] The countries with available information in the Penn World Table 9.0 are Bulgaria, Cyprus, Hungary, Malta, Poland, and Romania. We include Cyprus and Malta to be consistent with our approach when proxying the technology parameters α_{ij}. Depreciation rates by sector are unfortunately not available for the time period considered.

the technology parameters α_{ij} and the depreciation rate δ have only minor effects on the magnitude of our main parameter of interest.[39]

One way to circumvent the problem of having to calibrate the sector-specific technology parameters α_{ij} is to assume that these are constant across sectors and estimate the model in a single step. According to the production function introduced in Section IV, output growth in country i and sector j is given by

$$\Delta \ln Y_{ijt+1} = \rho\left(\frac{S_{ijt}}{Y_{ijt}}\right) + \eta\left(\frac{R_{ijt}}{Y_{ijt}}\right) + \theta \ln\left(\frac{A^F_{jt}}{A_{ijt}}\right) + \alpha_i \Delta \ln K_{ijt+1} + \beta_i \Delta \ln L_{ijt+1} + \lambda_{ij} + \pi_{it+1} + \mu_{jt+1} + \varepsilon_{ijt+1}, \tag{6}$$

where $\Delta \ln Y_{ijt+1}$ is the change in log value added, and where changes in the log capital stock and employment are directly included as control variables. Online Appendix Table A15 shows the results from this one-step approach where the dependent variable is the difference in the growth rates of gross value added between West and East Germany. Focusing on the OLS results, in columns 1 to 3 we assume that the technology parameters α_i and β_i are identical in both countries but relax the assumption of constant returns to scale (so β_i is no longer assumed to be equal to $1 - \alpha_i$). Introducing sequentially the patents gap and the initial log TFP gap to account for independent technology transfer for countries behind the technological frontier, the estimate increases from -0.033 to -0.054 and is thus comparable to our baseline finding. In columns 4 to 6, we further allow the coefficients on the capital and labor inputs to differ between West and East Germany, which leaves the main estimate almost unchanged.[40] Columns 7 to 18 report the corresponding IV estimates which, in the most comprehensive specification, resemble those reported in Table 3 but are relatively sensitive to the inclusion of the initial log TFP gap regressor. While the one-step approach is flexible as it neither requires a prior calibration of α and β nor imposes constant returns to scale, it is also restrictive relative to our main approach since it does not allow for sector-specific technology parameters.

D. *Alternative Outcomes*

One potential concern with the analysis so far is that our main outcome variable is a value-based measure of TFP and thus partly driven by changes in the prices of the underlying basket of output goods in each sector. In principle, the translation of the output data into constant prices accounts for these price effects but there remains some ambiguity regarding the valuation of new and upgraded products and their treatment in the relevant price indices. To address this concern, we provide

[39] As a further robustness check, we follow the approach of the Penn World Table and estimate the initial capital stock in each sector by multiplying the sector-specific output in the first available period (1950) with a constant capital/output ratio of 2.6 (compare Inklaar and Timmer 2013). This approach is argued to be more suitable for transition economies that are less likely to satisfy the steady-state assumption underlying the more standard approach. Not surprisingly given our long time series of gross fixed capital investment, we obtain very similar results using this alternative approach, with the main OLS estimate equal to -0.054 (0.012), the IV estimate based on old informants equal to -0.068 (0.025) and the exit-based IV estimate equal to -0.120 (0.037).

[40] Note that the estimated coefficients for the capital and labor inputs reported in column 6 are not statistically different between West and East Germany in absolute terms, with p-values of 0.55 and 0.51 respectively.

complementary evidence by studying the impact of industrial espionage on a purely quantity-based measure of output, taken directly from the East German Statistical Yearbooks. In the spirit of equation (6), we regress changes in the log physical quantity of 104 distinct products that were consistently produced in East Germany over the period 1970 to 1989 on our sector-specific measure of espionage inflows, controlling for year and sector-specific fixed effects as well as changes in the capital and labor inputs employed in each sector. Focusing on the OLS results first, columns 1 to 3 in the top panel of Table 6 show that in this balanced panel of products a one standard deviation increase in the inflow of information (1.40) generates an increase in physical output of around 5.0 log points. These quantity-based estimates suggest a positive effect of industrial espionage on the technical efficiency of production, broadly comparable in magnitude to the value-based estimates of -0.054 and -0.055 reported in columns 3 and 6 of online Appendix Table A15.

Changes in the quantity of a given set of output goods cannot capture any productivity effects arising from the introduction of new products, a frequent and often desired consequence of East Germany's espionage in the West. To investigate this issue, we relate sector-specific absolute and relative changes in the number of distinct products listed in the East German Statistical Yearbooks to our espionage inflow measure. The point estimates of 1.784 and 0.033 reported in columns 4 and 5 indicate that East Germany's industrial espionage had a significant positive effect on both the number of goods produced and the growth rate of the product portfolio.

In columns 6 to 8, we test whether East Germany's industrial espionage activities enhanced its ability to export to other countries. Using all available WTF data on the bilateral value of sector-specific exports, we find a positive but not significant impact on the growth rate in exports to East Germany's trading partners around the world (column 6). In columns 7 and 8, we run separate regressions for the sample of NATO member states (excluding West Germany) and all remaining countries.[41] The estimates suggest that East Germany's industrial espionage activities had no impact on its ability to export to the comparatively developed Western Bloc countries but might have had a positive effect on its exports to the rest of the world, with the corresponding estimate however not being statistically significant at conventional levels. Such a pattern would be in line with the historical observation that the acquired technological know-how from the West did ultimately not enable East Germany to compete with Western producers directly but strengthened its position in the rest of the world and the Eastern Bloc in particular.[42]

[41] Besides West Germany, for whom imports from East Germany are not recorded in the WTF, the remaining 15 NATO member states at the time were Belgium, Canada, Denmark, France, Greece, Iceland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Turkey, the United Kingdom, and the United States. The WTF sample for the rest of the world comprises 91 countries. The point estimates in columns (6) to (8) of Table 6 are very similar when we additionally include importing country fixed effects.

[42] Since the WTF data do not include information on the value of East German exports to West Germany, an important omission given the latter's role as East Germany's main trading partner in the West, we collect export data on 86 distinct products belonging to 9 sectors from the East German Statistical Yearbooks and regress changes in the log value of product-specific exports on our sector-specific espionage inflow measure. The resulting estimate of 0.064 reported in column 1 of online Appendix Table A16 implies that a one standard deviation increase in the inflow of information increases exports by 9.0 log points. However, since these export data only cover a limited set of sectors and are, at least in principle, subject to potential manipulation prior to publication, this finding should be viewed with some caution.

Table 6—Alternative Outcomes

	Quantity Output			New Products		Exports		
				Δ	$\Delta\ln$	World	NATO	Rest world
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OLS								
Espionage	0.035	0.036	0.036	1.784	0.033	0.106	0.005	0.148
	(0.016)	(0.020)	(0.020)	(0.640)	(0.018)	(0.063)	(0.079)	(0.092)
GDR patents/Y		yes	yes	yes	yes	yes	yes	yes
log TFP gap			yes	yes	yes	yes	yes	yes
p-value WB	0.038	0.097	0.091	0.032	0.078	0.197	0.954	0.243
R^2	0.07	0.07	0.07	0.57	0.55	0.06	0.18	0.04
Observations	1,558	1,558	1,558	240	240	5,757	1,863	3,894
IV—old informants								
Espionage	0.071	0.080	0.081	2.360	0.051	0.164	0.106	0.160
	(0.028)	(0.032)	(0.033)	(1.487)	(0.020)	(0.225)	(0.349)	(0.249)
GDR patents/Y		yes	yes	yes	yes	yes	yes	yes
log TFP gap			yes	yes	yes	yes	yes	yes
p-value WB	0.021	0.034	0.030	0.308	0.084	0.640	0.889	0.684
F-statistic	11.1	23.8	31.2	73.5	73.5	95.7	89.3	92.5
Observations	1,558	1,558	1,558	240	240	5,757	1,863	3,894
IV—exit of informants								
Espionage	−0.032	−0.032	−0.027	−1.704	−0.003	1.235	2.364	0.619
	(0.025)	(0.024)	(0.019)	(2.741)	(0.038)	(0.405)	(0.806)	(0.336)
GDR patents/Y		yes	yes	yes	yes	yes	yes	yes
log TFP gap			yes	yes	yes	yes	yes	yes
p-value WB	0.257	0.200	0.175	0.630	0.947	0.117	0.085	0.201
F-statistic	10.3	22.5	30.0	32.4	32.4	20.3	15.5	21.6
Observations	1,246	1,246	1,246	192	192	3,834	1,329	2,505

Notes: Sample based on 3-year intervals and overlapping observations for the period 1970 to 1989. All regressions control for changes in the sector-specific log capital stock and employment as in equation (6), and include time- and sector-specific fixed effects. All dependent variables are measured as changes between periods t and $t+3$. The instrumental variables are described in Section VA. In columns 1 to 3, the estimation is based on a balanced sample of 104 products observed consistently in the East German Statistical Yearbooks over the period 1970 to 1989. In each of the three columns, the dependent variable is the product-specific change in the log physical quantity produced. In column 4, the dependent variable is the sector-specific absolute change in the number of distinct products listed in the East German Statistical Yearbooks. In column 5, the dependent variable is the sector-specific change in the log number of distinct products. In column 6, the dependent variable is the country-specific change in log exports of East Germany (measured in constant 1995 dollars) using information from all available importing countries included in the World Trade Flows 1962–2000. In columns 7 and 8, the regressions are run separately for importing NATO countries and all other countries respectively. In columns 4 to 8, observations are weighted by the average number of workers in a sector. Standard errors are clustered at the sectoral level and shown in parentheses. p-value WB denotes p-values, relating to the espionage estimate, from Cameron, Gelbach, and Miller's (2008) wild cluster bootstrap-t procedure using 999 replications.

In online Appendix Table A16, we also provide evidence for a significant negative effect of the inflow of information from the West on East Germany's own patenting activities, consistent with reports in Macrakis (2008) of industrial espionage essentially crowding out overt R&D.[43] In fact, internal estimates by the Stasi itself suggested that its industrial espionage activities had saved the East German economy about 75 million East German mark in R&D expenditures.

The IV results based on old informants reported in the middle panel of Table 6 broadly mirror the findings of the OLS specifications but with generally larger

[43] In contrast, we find no evidence of an impact of East German industrial espionage on West German patenting, with an OLS point estimate of 0.005 (0.008).

estimated effects. In contrast, the exit-based IV results reveal quite a different pattern. While no longer providing any evidence for an impact on the physical quantities produced or the diversity of the output basket, they point toward a significant positive effect on East Germany's exports, in particular to NATO member states. This could be due to the specific type of information generated by exiting informants, who were primarily working in the high-tech electronics sector and tended to provide unusually valuable information. Variation in the inflow of such information may then have affected East Germany's ability to export even on the world market. Overall, the results in Table 6 point toward a real effect of the Stasi's industrial espionage on East Germany's production structure, increasing its efficiency, diversity and, with some reservation, international scope.

E. *Quality of Information*

Given the large volume of information received during the 1970s and 1980s, it is likely that relatively few pieces contained sufficiently novel and utilizable information to generate noticeable productivity gains in East Germany's economy. To account for this, we exploit the fact that in 1980 the Stasi started to systematically evaluate the quality of all incoming information on a scale from 1 to 5. Overall, 40.1 percent of all pieces of information in our sample were qualitatively assessed in that way, with the vast majority receiving a value of 3 ("average value," 66.1 percent), a fair amount receiving a value of 2 ("valuable," 23.8 percent) and only a small fraction receiving an assessment of 1 ("very valuable," 2.8 percent).

Based on this information, we estimate an extended specification of our empirical model in which we break down the overall measure of sector-specific espionage inflows into separate quality components. Besides the numerical quality assessments from 1 to 5, we construct a residual category labeled "missing" which pools all pieces of information that were either given the label "no assessment" upon arrival at the Stasi (1.5 percent of all pieces of information) or genuinely not quality-assessed (58.4 percent). Because of the frequency of missing quality information and to avoid having to discard most of the information collected before 1980, we implement an imputation algorithm in which we replace any missing quality assessment with an informant-based predicted measure of quality. Specifically, we regress the observed quality assessments in the data on a full set of informant fixed effects and a cubic function of experience, calculated as the accumulated years since an informant's first appearance in the SIRA database (see the left panel of online Appendix Figure A3). Based on the results from this regression, we then predict an informant-specific and experience-adjusted quality measure for each piece of information with missing quality assessment, rounding the predicted values to the closest integer value. These imputed measures allow for the fact that informants may get better at providing high-quality information over time, either through learning or through improved access to relevant material, for example as a result of career progression. Online Appendix Figure A11 shows the distribution of quality assessments both before and after our imputation procedure, where we aggregate for better readability the quality values 1 and 2 into a "high" category, value 3 into a "medium" category, and values 4 and 5 into a "low" category. Overall, after the imputation, the coverage of quality information

Table 7—Quality of Information

	Δ log TFP gap			Δ log output per worker gap		
	Main spec (1)	Observed quality (2)	Imputed quality (3)	Main spec (4)	Observed quality (5)	Imputed quality (6)
Espionage	−0.052			−0.039		
	(0.012)			(0.017)		
Quality: no value		−2.003	−0.030		−1.156	0.100
		(1.728)	(0.205)		(1.895)	(0.197)
Quality: low value		−0.034	−0.223		−0.219	−0.258
		(0.614)	(0.063)		(0.660)	(0.078)
Quality: average value		0.015	−0.020		−0.030	−0.010
		(0.109)	(0.036)		(0.131)	(0.044)
Quality: valuable		0.059	0.136		0.248	0.212
		(0.281)	(0.083)		(0.390)	(0.138)
Quality: very valuable		−1.391	−1.570		−1.603	−1.807
		(0.692)	(0.554)		(0.975)	(0.621)
Quality: missing		−0.072	−0.060		−0.051	−0.030
		(0.021)	(0.046)		(0.025)	(0.047)
p-value WB	0.011			0.125		
p-value WB: no value		0.300	0.871		0.586	0.649
p-value WB: low value		0.952	0.041		0.733	0.048
p-value WB: average value		0.894	0.606		0.865	0.842
p-value WB: valuable		0.839	0.145		0.630	0.291
p-value WB: very valuable		0.161	0.040		0.319	0.059
p-value WB: missing		0.042	0.273		0.161	0.586
R^2	0.56	0.56	0.57	0.51	0.52	0.54
Observations	240	240	240	240	240	240

Notes: Sample based on 3-year intervals and overlapping observations for the period 1970 to 1989. All regressions include time- and sector-specific fixed effects, the patents gap, and the initial log TFP or output per worker gap as additional regressors. Observations are weighted by the average number of workers in a sector. The dependent variable is the change in the log TFP gap between West and East Germany over the period t to $t + 3$ in columns 1 to 3 and the change in the log output per worker gap over the period t to $t + 3$ in columns 4 to 6. Prior to the imputation procedure, 0.6 percent of the pieces of information in the sample were given a quality assessment of *no value*, 2.3 percent of *low value*, 26.5 percent of *average value*, 9.6 percent of *valuable*, and 1.1 percent of *very valuable*, with the remaining 59.9 percent *missing*. Standard errors are clustered at the sectoral level and shown in parentheses. *p*-value WB denotes *p*-values, relating to the espionage estimate, from Cameron, Gelbach, and Miller's (2008) wild cluster bootstrap-*t* procedure using 999 replications.

improves substantially, from 40.1 percent to 80.3 percent, distributed relatively evenly over the period considered.

Table 7 shows the impact of the different quality types of information on the log TFP gap (left panel) and the log output per worker gap (right panel) between West and East Germany, where columns 1 and 4 once more restate our baseline OLS results for comparison. The regressions underlying columns 2 and 5 are based on the observed information in the data, with little quality input prior to the 1980s and consequently many observations with missing assessments. Despite this lack of information, there is already some indication that the marginal effect of the highest quality information far exceeds that of all other groups. Columns 3 and 6, which are based on the sample with imputed quality information, confirm these results, showing that the largest impact of industrial espionage on the productivity gap between West and East Germany is due to the inflow of "very valuable" information, with point estimates of −1.570 for the log TFP gap and −1.807 for the log output per worker gap. Somewhat surprisingly, in this specification the relationship between quality and impact on productivity growth is not monotonic, with the low value group, which makes up 5.8 percent of all quality-assessed pieces of information in the sample, also showing significant negative effects on relative productivity growth. However, the parameters for the inflows of low quality information, average quality information and valuable information are much smaller in magnitude and, in the latter two cases, which comprise the bulk of information in the data, statistically not significant. These findings suggest that a substantial part of the information received by the Stasi was probably dispensable and that the positive effects on East German productivity growth were primarily driven by relatively few select pieces of information.[44]

F. *Heterogeneity*

In this section, we study heterogeneous effects along two important dimensions: the initial TFP gap and the imports gap. To this end, we extend the baseline OLS specification by including interactions between our inflow measure and indicator variables for different quartiles of the initial log TFP gap, allowing these indicator variables to substitute for the linear log TFP gap term in equation (4). Panel A of Figure 6 depicts the estimates of the four interaction effects. Evidently, industrial espionage was more effective in narrowing the productivity gap in industries that were technologically closer to their West German counterparts. In these cases, East German researchers and engineers were presumably better able to integrate the newly acquired knowledge into their own production processes, suggesting that a sufficiently high absorptive capacity is a prerequisite for the successful exploitation of espionage-based scientific-technical information. This result contrasts with existing studies on the returns to standard forms of R&D which suggest larger returns in industries further away from the frontier (Griffith, Redding, and Van Reenen 2004).

As a second relevant dimension of heterogeneity, we examine the interaction between industrial espionage and relative import barriers by interacting our inflow measure with different quartiles of the West-to-East import intensity gap (including as before the four main effects as additional regressors in the model). If industrial espionage serves as a form of technology transfer when regular channels such as trade are not available, one might expect stronger effects in cases where the gap between West and East German import intensities is larger. Panel B of Figure 6 shows that there is no evidence for this hypothesis. The marginal effects across the four quartiles are similar in magnitude (-0.049, -0.057, -0.040, and -0.077) and not statistically distinguishable from each other. This suggests that industrial espionage was equally useful in sectors that were relatively open to international trade as in sectors where East Germany's ability to import from abroad was more restricted. While in the latter case industrial espionage may have substituted to a higher degree for trade-based technology transfers, complementarity between technological know-how and actual foreign imports may have compensated for this effect, leading to overall similar impacts across sectors.

[44] We do not report IV specifications since, with six endogenous variables, these do not yield meaningful results.

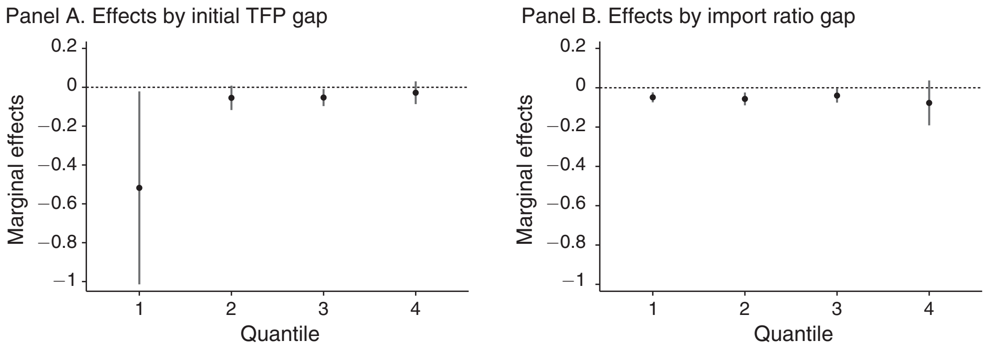

Figure 6. Heterogeneous Effects of Industrial Espionage

Notes: The graphs plot the marginal effects from an OLS specification in which the inflow of information variable is interacted with the quartiles of the initial log TFP gap (panel A) and the initial import intensity gap (panel B). 95 percent confidence intervals are constructed from standard errors clustered at the sectoral level. The corresponding wild cluster bootstrap *p*-values are 0.111, 0.032, 0.069, and 0.398 for the estimates shown in panel A, and 0.016, 0.014, 0.068, and 0.298 for the estimates shown in panel B.

G. *Counterfactual Simulations*

Our empirical results show that the Stasi's industrial espionage program had a positive effect on East Germany's productivity growth during the 1970s and 1980s. Based on our estimates, we are able to simulate how the TFP gap between West and East Germany would have evolved in the absence of industrial espionage. For this purpose, we set S_{Ejt}/Y_{Ejt} to zero for all industries and time periods and, starting with the first 3-year period 1970–1972, forward-predict counterfactual log TFP gaps between West and East Germany. As suggested by our main findings, in the absence of industrial espionage, TFP growth in East Germany would have been lower although part of this effect is counteracted by the fact that lower future levels of TFP give rise to a positive effect on subsequent TFP growth by increasing the distance to the productivity frontier (as indicated by the negative coefficient of -0.564 on the log TFP gap regressor in column 3 of Table 2).

Figure 7 displays the results from these counterfactual simulations. To facilitate interpretation, we transform actual and counterfactual log TFP gaps into the ratio of East German TFP to West German TFP. The solid line in panel A of Figure 7 depicts the development of an aggregate measure of the actual TFP ratio between 1972 and 1989, which we construct from the employment-weighted average of the sector-specific log TFP gap profiles. During the 1970s, East Germany's productivity increasingly fell behind West Germany's, with relative TFP declining from 21.4 percent in 1972 to 19.2 percent in 1979. During the 1980s, this trend was reversed with relative TFP growing steadily, reaching 21.8 percent in 1989.[45] As depicted by the short-dashed line, in the absence of industrial espionage, the East/West TFP ratio would amount to only 18.9 percent at the end of the time period, a 13.3 percent

[45] The difference between the average East/West TFP ratio we obtain of 21.8 percent and the corresponding output per worker ratio of about 44 percent (compare Section IIB) is primarily due to the much higher capital intensity K/Y in East German industries, a finding also documented in Burda and Severgnini (2018). In our sample, the average capital intensity in East Germany is 4.09 compared to 2.27 in West Germany.

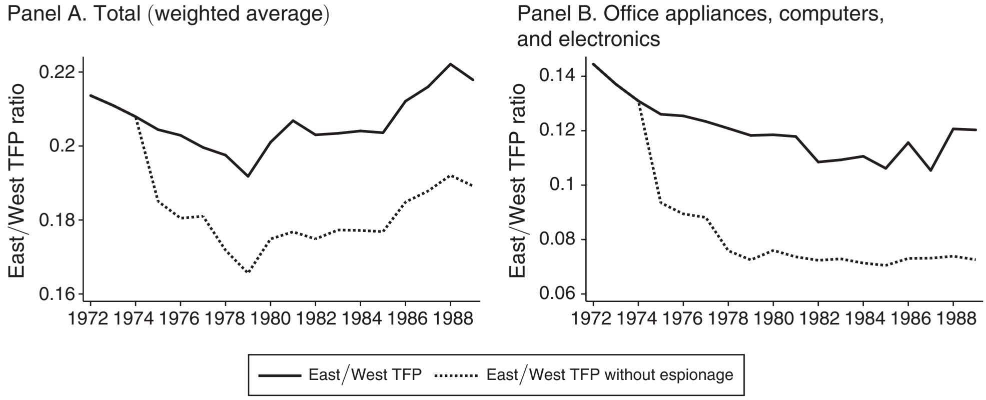

Figure 7. Counterfactual Simulations

Notes: The panels depict the counterfactual East/West TFP ratios aggregated across all industry sectors (panel A) and specifically for the *Office Appliances*, *Computers, and Electronics* sector (panel B). To aggregate across sectors, we take the employment-weighted averages of the actual and counterfactual log TFP gaps before transforming them into East/West TFP ratios. The counterfactual simulations are based on the empirical results reported in column 3 of Table 2.

decline relative to the baseline.[46] Overall, industrial espionage thus played a noticeable but, given the magnitude of the actual TFP gap, quantitatively modest role in bringing East Germany's productivity closer to its West German counterpart.

Panel B of Figure 7 shows the corresponding actual and counterfactual TFP ratios for the *Office Appliances*, *Computers, and Electronics* sector, the sector most intensively targeted by East Germany's industrial espionage. Contrary to the aggregate development, in this sector the productivity gap widened continuously over time, from 14.4 percent in 1972 to 12.0 percent in 1989. In the absence of industrial espionage, this divergence would have been significantly more pronounced, with the counterfactual TFP ratio declining to 7.3 percent in 1989. Evidently, in this fast-changing sector, industrial espionage allowed East Germany to at least keep up with productivity growth in the West. Online Appendix Figure A12 shows the corresponding graphs for all other sectors.

The counterfactual simulations show that industrial espionage benefited the East German economy by accelerating productivity growth. However, they do not speak to the question of whether the resources committed to espionage were efficiently used. While a full cost-benefit analysis is beyond the scope of this paper, also due to the lack of reliable information on the cost side, we can use existing estimates to get at least a tentative idea about this important question. As it turns out, every year the Stasi itself produced estimates of the economic benefit attributable to the utilization of espionage information. According to the long-term head of the HVA's Sector for Science and Technology, Horst Vogel, these annual benefits amounted to around 300 million East German mark in the 1970s and increased substantially to more than 1.5 billion East German mark at the end of the 1980s (Müller, Süß, and Vogel 2009).

[46] Due to the use of 3-year intervals and the lag structure between dependent and independent variable, the first time period in which actual and counterfactual TFP in East Germany can diverge is 1975.

Our own results point to even larger annual benefits of around 10.1 billion euros, which translate into around 16.1 billion Deutsche Mark in 1989.[47] Note that this estimate reflects the annual benefit from all past espionage information received, while the internal estimates of the HVA likely refer to the benefit from the specific information collected in a given year. On the cost side, the last head of the HVA, Werner Großmann, stated in front of a parliamentary committee in the 1990s that the annual budget for operational purposes of the HVA at the end of the 1980s amounted to around 17.5 million East German mark and 13.5 million Deutsche Mark, which translate into approximately 11.0 million euros (in 1995 prices). While these figures should naturally be viewed with caution, taken together they suggest a very high return on the investment in industrial espionage.[48]

VI. Conclusion

This paper presents the first systematic evaluation of the economic returns to state-sponsored industrial espionage. The Stasi archives and their rich information on industrial espionage provide a unique opportunity for studying this question and, more broadly, shed light on the role of international knowledge flows for productivity growth. Our empirical findings show that the returns to industrial espionage were substantial, enabling East Germany's economy, at least to some extent, to keep up with productivity growth in the West.

Arguably, few contemporary intelligence agencies have been able to make industrial espionage as effective a tool as the Stasi during the Cold War. While the benefits of industrial espionage may have declined since then due to more integrated international markets and easier access to new ideas through legitimate channels, the costs have likely fallen even more in the wake of the digital revolution and the emergence of cyber-espionage as a new and comparatively cheap method of illicit technology transfer. Most developed countries nowadays therefore view industrial espionage as a severe and growing threat to their economies,[49] making the topic as relevant today as it was at the height of the Cold War.

Due to the particular institutional setting in East Germany during the period analyzed, there are several issues that could limit the external validity of our findings. These include the discrepancy between East Germany's centrally planned economy

[47] These figures are constructed as follows. We multiply the actual total gross value added across the 16 industry sectors in East Germany in 1989 (76,055 million euros, measured in 1995 euros) by 0.867, the ratio of counterfactual to actual East German TFP in that year, computed using the corresponding East/West TFP ratios depicted in panel A of Figure 7 and assuming no significant effect of industrial espionage on West German TFP. We then take the difference between the resulting counterfactual gross value added (65,940 million euros) and the actual gross value added (76,055 million euros) and convert it into current Deutsche Mark in 1989 using the exchange rate between Deutsche Mark and the euro (1.95583:1) and changes in the consumer price index in Germany between 1989 and 1995 (+22.5 percent). Note that at the end of the 1980s, the unofficial exchange rate between East German mark and deutsche mark was around 4.4:1.

[48] Given this high return, a natural question arising is why East Germany did not invest even more resources in its espionage activities in the West. Online Appendix Figures A1 and A3 show that there were indeed ongoing attempts to further expand these activities, with both the annual inflows of information and the number of new informants increasing rapidly from the end of the 1970s onward. An important limiting factor, however, appears to have been the ability to identify and successfully recruit new reliable informants. Even though the Stasi was very systematic in identifying and prescreening potential candidates, it is estimated that between 75 and 90 percent of the individuals approached declined to work for the Stasi (Herbstritt 2007, p. 117).

[49] See, for example, ONCIX (2011) or Kasper and Thürnau (2014).

and today's more market-based economies, the extensive trade embargoes against the entire communist bloc at the time which severely restricted standard forms of technology transfer, and the fundamental shift in the technology of spying in recent decades away from human intelligence toward IT-based methods. However, the process through which newly acquired information is translated into productivity growth today might not differ that much from the process in place in East Germany at the time of the Cold War, especially in countries characterized by strong centralized governments like China and Russia. While the effectiveness of East Germany's industrial espionage program may have been exceptional, this effectiveness was arguably due to the Stasi's outstanding ability to recruit and plant informants in relevant positions in West Germany, greatly facilitated by the close historical links between both countries and the role of ideology as an important (and cheap) motive for collaboration. Whether or not the marginal effect of additional information on productivity, the parameter at the center of this analysis, is different today than it was 40 years ago is a more difficult question to answer. Despite the Stasi's high level of proficiency, we would therefore not necessarily view our results as an upper bound of the effect of industrial espionage on productivity.

One issue that this study cannot shed light on is the espionage that takes place directly between individual firms, often operating in the same industry and country. This type of industrial espionage, also referred to as corporate espionage, is frequently considered to be at least as important as industrial espionage on behalf of foreign governments. There are many dimensions in which these types of espionage differ. Because of the stronger competition in key markets, corporate espionage tends to have more negative effects on affected firms, for instance through losses in market share, thus generating both knowledge spillovers and business-stealing effects at the same time. Corporate espionage also tends to be more targeted and therefore possibly more productive, at least in comparison to the, at times, relatively indiscriminate gathering of information by the Stasi. The handling of informants is also likely to differ substantially, with materialistic motives playing a much more important role in corporate espionage. Finally, many legal systems make a clear distinction between the two, generally stipulating more severe sentences for state-sponsored industrial espionage. How these fundamental differences affect the returns to industrial espionage is an open question that has to remain unanswered for the time being.

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