Industrial Espionage and Productivity

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Abstract

In this paper, we investigate the economic returns to industrial espionage by linking information from East Germany's foreign intelligence service to sector-specific gaps in total factor productivity (TFP) between West and East Germany. Based on a dataset that comprises the entire flow of information provided by East German informants over the period 1970-1989, we document a significant narrowing of sectoral West-to-East TFP gaps as a result of East Germany's industrial espionage. This central finding holds across a wide range of specifications and is robust to the inclusion of several alternative proxies for technology transfer. We further demonstrate that the economic returns to industrial espionage are primarily driven by relatively few high quality pieces of information and particularly strong in sectors that were closer to the West German technological frontier. Based on our findings, we estimate that the average TFP gap between West and East Germany at the end of the Cold War would have been 9.5% larger had the East not engaged in industrial espionage.

JEL Classification: D24, F52, N34, N44, O30, O47, P26

Keywords: Espionage, Productivity, R&D, Technology Diffusion

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"The Ministry for State Security has the goal of acquiring, in steadily increasing volume, scientific-technical information and documents from West Germany and other capitalist countries." – Erich Mielke, Minister of State Security (1957-1989), *BStU, Policy Documents. DA, 3/55/DSt 100938*

1 Introduction

Throughout history, industrial espionage[1] has remained a pervasive channel for technology transfer. Possibly the earliest recorded incidence of state-sponsored industrial espionage occurred in the 6th century AD, when two Nestorian monks successfully smuggled silkworm eggs, likely hidden in bamboo canes, from China into the Byzantine Empire. This daring feat, an important juncture in the economic history of the Early Middle Ages, led to the breaking of two monopolies: that of Chinese silk production and that of the Persian silk trade with the West. As a result, Byzantine silk became one of the Empire's most profitable commodities while also providing a valuable medium of exchange, and several cities developed into major textile centers as a result (Norwich, 1990; Laiou, 2002). In the late eighteenth and early nineteenth centuries, "[t]he United States emerged as the world's industrial leader by illicitly appropriating mechanical and scientific innovations from Europe" as "American industrial spies roamed the British Isles, seeking not just new machines but skilled workers who could run and maintain those machines" (Ben-Atar, 2004).

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. Undoubtedly, the secret nature of the practice obscures its economic significance which, in terms of costs, is believed to be substantial. For example, industrial espionage is currently estimated to cost the US economy around 19 billion dollars per year[2] and the German economy around 11.8 billion euros per year (Corporate Trust, 2014), both figures from the lower end of a rather wide range of available estimates. In comparison to the costs, the economic benefits accruing to those countries actively engaging in industrial espionage are even more opaque. Its persistent and widespread use, however, 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 of our analysis 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 empirical work 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, which survived the political turmoils after the fall of the Berlin Wall in November 1989 only through a stroke of luck, includes detailed information on 189,725 individual pieces of information received by the East German Ministry for State Security

[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 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, 2008).

[2] Source: FBI, 2013, https://leb.fbi.gov/2013/october-november/economic-espionage-competing-for-trade-by-stealing-industrial-secrets.

(MfS, commonly referred to as *the Stasi*), including their precise date of receipt, the registration numbers and 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 industry sector(s) it pertains to. 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 both West and East Germany between 1970 and 1989. In our main estimation equation, we regress changes in sectoral log TFP gaps between West and East Germany (equivalent to sectoral 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. A one standard deviation increase in the covert inflow of information results in a 6.9 percentage point decrease of the log TFP gap and a 5.5 percentage point decrease in the log output per worker gap between West and East Germany. These results are robust across a large number of specifications and little affected if we allow for alternative channels of technology transfer. To address potential endogeneity concerns, we employ an instrumental variable strategy in which we either only utilize information generated by informants who were already active at the beginning of the sample period or exploit the sudden discontinuation of certain informants as providers of information as an exogenous source of variation in the sector-specific inflows of information. Both instruments lead to results somewhat larger in magnitude than our baseline OLS estimates. Through a series of placebo estimations we show that industrial espionage had, as expected, no effect on the log TFP gap between West Germany and a number of other developed economies, suggesting not only that the information obtained by East Germany was not shared with other Western countries but also that there is no systematic link between West German TFP growth and the amount of information collected by East German informants.

Analyzing different dimensions of heterogeneity, we document that the positive effect on East German productivity growth is driven primarily 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. Our findings further show that industrial espionage tended to crowd out investments in regular overt R&D in East Germany. To conclude, we run 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 actual average TFP gap between West and East Germany, which amounted to 189% in 1989, would have been 9.5% larger (207%) 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 TFP gap in 1989 would have widened by 35.1% (from 416% to 562%) 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 finally indicates that the net return of industrial espionage was substantial, with annual benefits of the order of 4.6 billion euros contrasting with running costs of around 11.0 million euros.

The main contribution of our paper is to provide the first ever empirical assessment of the role of industrial espionage for technological progress. In doing so, our paper touches upon several relevant strands of the economics literature. Viewing industrial espionage as a means of acquiring new scientific-technical knowledge, our study relates to the literature on the role of innovation in explaining productivity growth (e.g. Griliches and Lichtenberg, 1984; Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992; Howitt, 2000). This literature finds predominantly large economic returns to R&D but has so far remained silent on the contribution of industrial espionage. Since industrial espionage inherently involves the flow of technological knowledge from the targeted country to the perpetrating country, our work also speaks to the literature studying relevant overt channels of technology diffusion and knowledge spillovers such as international trade (e.g. Coe and Helpman, 1995; Eaton and Kortum, 1999; Cameron, Proudman and Redding, 2005, Lucas, 2009; Alvarez, Buera and Lucas, 2013; Buera and Oberfield, 2016), foreign direct investment (e.g. Aitken and Harrison, 1999; Javorcik, 2004; Blalock and Gertler, 2008; Keller and Yeaple, 2009; Guadalupe, Kuzmina and Thomas, 2012; Fons-Rosen, Kalemli-Ozcan, Sørensen, Villegas-Sanchez and Volosovych, 2013), and international migration (e.g. Hunt and Gauthier-Loiselle, 2010; Poole, 2013; Moser, Voena and Waldinger, 2014), all channels that were largely absent in the East-West-German context of the Cold War period.[3] In analyzing the heterogeneous effects of industrial espionage across East German industry sectors and its impact on East Germany's own R&D efforts, we also touch upon the literatures on absorptive capacity (e.g. Cohen and Levinthal, 1989; Aghion and Jaravel, 2015) and the role of 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). Given our finding that industrial espionage to a large extent substitutes for overt forms of innovation, in this case measured by patents, our paper also relates to the literature on the determinants of patents as a source of innovation and economic development (e.g. Sokoloff, 1988; Moser and Voena, 2012; Moser, 2013). A key finding in this literature is that regulation of patents determines the direction of technical change and that the ensuing market responses tend to affect the patterns of comparative advantage. In our case, the prevalence of industrial espionage in East Germany may very well have distorted the incentives to conduct innovation that would conform with standard patent regulation.

Besides the broader innovation literature, our paper 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) exploit 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, confirming earlier cross-sectional results by Jacob and Tyrell (2010) and Friehe, Pannenberg and Wedow (2015). These papers thus focus on another main activity of the Stasi, the mass surveillance of East Germany's own citizens. Other examples for the adverse effects of secrecy come from the archival study of the former Soviet Union's intelligence agency, the KGB, which has revealed how secrecy incurred broad efficiency

[3] A lingering identification challenge in past studies on the impact of R&D on growth through spillovers has been separating the positive effects of technology spillovers from the negative business stealing effects through product market rivalry (Bloom, Schankermann and Van Reenen, 2013). In our setting, the limited product market rivalry between East and West German industries allows us to effectively estimate effects of technology spillovers separately from any business stealing effects. In line with this argument, we demonstrate the absence of any effects of East German industrial espionage on TFP growth in West German industries (see Table 7).

costs (Harrison, 2008), specifically via the transaction costs involved in accounting for secrets (Harrison, 2013), and how KGB-induced labor market regulation resulted in adverse selection for talent (Harrison and Zaksauskiene, 2016). 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 systematically increased imports from the United States in those countries in which the CIA successfully helped to install a new leadership (Berger, Easterly, Nunn and Satyanath, 2013).

Outside of economics, there is of course a more extensive literature on espionage by historians, typically focusing on specific case studies or the successes and failures of individual spies (e.g. Macrakis and Hoffmann, 1999; Macrakis, 2004; Friis, Macrakis and Müller-Enbergs, 2009). Regarding East German espionage in the West, Herbstritt (2011) synthesizes available court material from numerous legal cases against former Western informants of the Stasi in the post-unification period to provide a comprehensive picture of the recruitment strategies of the Stasi and the social structure of its network of informants in West Germany, complementing the extensive work on the Stasi and its foreign intelligence branch by Müller-Enbergs (1996, 1998, 2008, 2011). In terms of content, the work by Macrakis (2008) comes closest to the type of question we analyze in this paper. In her book, she argues based on previously confidential files from the Stasi archives 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. As more and more resources were poured into stealing rather than generating technologies, East Germany's own innovation ultimately suffered in her view. Yet as late as 1989, East Germany was also seen by some as "Communism that works" – "the Communist world's high-technology leader...its capital goods known for quality workmanship".[4] While our empirical analysis provides corroborating evidence for a negative effect of industrial espionage on East Germany's own R&D activities, our main results show that once the entirety of the espionage-related information flows from the West to the East 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 2 provides the historical context in which East Germany engaged in industrial espionage in the West. Section 3 describes the data sources used in the paper. Section 4 introduces the empirical framework and estimation strategy. Section 5 presents the main results of our analysis. Section 6 concludes the paper.

2 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 (Jackson, 2001). 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 export controls on an ever more extensive list of goods bound for the communist East. Increasingly, these included not just goods from the military and nuclear sectors but also industrial "dual-use" products characterized

[4] "East Germany Losing Its Edge", The New York Times, May 15, 1989, `http://www.nytimes.com/1989/05/15/business/east-germany-losing-its-edge.html?pagewanted=all`

by advanced technologies which could, at least in principle, be used for military purposes. While technology transfer from the West to the East was a contentious issue during most of the Cold War era, efforts to curtail it further accelerated following the election of Ronald Reagan as president of the United States in 1981. 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), which was founded in 1951 and, between 1952 and 1986, led by the famous spy chief Markus Wolf. Within the HVA, the department 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 (Müller-Enbergs, 2010) 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. The immediate geographic proximity and the initially open border to West Germany allowed the Stasi to expand its intelligence network there from relatively early on, often under the cover of the substantial East-West migration at the time. This primary method of infiltrating the West changed with the construction of the Berlin Wall in 1961 and the accompanying heightened scrutiny at the inner German border, after which the systematic recruitment of new informants in West Germany, in particular at universities, took a more prominent role. Most of the informants working for the Stasi in the West were male salaried employees, predominantly engineers or employees with science degrees, although a number of sources also worked in personnel departments or as businessmen (Macrakis, 2008; Herbstritt, 2011). 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") at AEG/Telefunken, who worked as an engineer, and Peter Köhler (codename "Schulze"), who worked for Texas Instruments.[5]

While not generalizable, existing historical case studies provide some insights into the process of industrial espionage against specific firms and industries. For example, past research comparing the West German company Carl Zeiss Oberkochen with its East German counterpart Carl Zeiss Jena (CZJ) has argued that the latter achieved "remarkable competence" in innovation despite operating in a Socialist environment (Kogut and Zander, 2000). Today, however, it is known that a significant part of CZJ's innovation input came from industrial espionage disseminated via the Sector for Science and Technology of the Stasi. According to Macrakis and Hoffmann (1999), between 1977 and 1989 the company received materials valued at more than 8 million Deutsche Mark from the Stasi. The close cooperation between CZJ and the East German foreign intelligence service increased to the point where a whole Stasi branch office was set up at CZJ to provide the firm directly with information and material. While not all East German companies had in-house Stasi branches like CZJ, the process of submitting technology wish-lists to the intelligence agency

[5]For a comprehensive analysis of the recruitment, motivation and social background of the Stasi's West German informants, see Knabe (1999), Müller-Enbergs (1998, 2008, 2011) and Herbstritt (2011).

seems to have been a recurring phenomenon.

Macrakis (2004) illustrates how industrial espionage was carried out at the time by describing East Germany's attempts to produce the 1-megabit chip:

> *"On 27 November 1986, Professor Dr. Dr. h.c. Wolfgang Biermann applied for 'documents and samples of the 1-megabit chip' as part of the development topic and state program 'Höchstsintegration' ('supreme integration', the codename for the 1-megabit project). His application was given the number 51,87,00086 (51 stood for Carl Zeiss Jena, '87 the year it was to be realized and 86 the number of the application). SIRA documents show that several pieces of information helped to 'partly realize' this application. On 3 September 1988, a source codenamed 'Joker', run by SWT XV acquired the technology for the 1-megabit chip. On 27 May 1988, 'Zelter' from SWT XV delivered logic technology and information on the manufacture of highly integrated circuits and on the 22 June 1988 a '1MBYTE DRAM' among others. Robotron also put in an order for information on the 1-megabit chip and received material."*

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 and cost-reducing use of energy, new and efficient processing techniques for raw materials, the optimal utilization of by-products as secondary raw materials, research findings and processes of the chemical industry for higher finishing grades of primary raw materials and the development of synthetic materials and chemicals, and findings from the field of biology and microbiology for the application of biosynthesis and biogenetics in plant and animal production (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. By 1970, East German electronics experts had already acquired and reverse engineered more than a dozen computers such as the IBM 360, and by 1973 the Dresden-based VEB Robotron was producing computers "at a rate of eighty to one hundred per year" (Macrakis, 2008).[6]

Meanwhile, Western intelligence in East Germany remained by most accounts behind its East German counterpart in recruiting reliable informants, especially so in the economic sector. Partly, this may have been the result of priorities, topically as well as methodologically, as Western espionage focused disproportionately on political and military – rather than economic – espionage, using signals intelligence more effectively than human intelligence. In addition, the West German foreign intelligence agency (*Bundesnachrichtendienst*, BND) was heavily compromised by moles in the early years of the Cold War (Schmidt-Eenboom, 2009). Furthermore, Stasi officials have often boasted of the degree to which the Western intelligence sources in East Germany were, in fact, double agents, with one general putting that number at around 90% (Schmidt-Eenboom, 2009). It is therefore unlikely that in those instances where Western espionage activities were successful in East Germany, they were related to the economic sector or any substantive technology transfers

[6] As a reflection of the computer industry's importance, "IBM" is the 29th most common keyword appearing in the SIRA database, with the keywords "Microelectronics," "Software," "Computer Science," and "Electronic Data Processing" in seventh, eight, ninth, and eighteenth place, respectively (compare Table A-1).

from the East to the West. As such, the transfer of technologies was overwhelmingly a one-way street.

3 Data

The empirical analysis in this paper relies on a number of different data sources, with two being of particular importance. First and foremost, we exploit data on industrial espionage, taken directly from the HVA's main electronic database SIRA (*System der Informationsrecherche der Hauptverwaltung Aufklärung*), which is currently maintained by the The Agency of the Federal Commissioner for the Stasi Records (BStU). In addition, we use data recently published by Heske (2013) on output, employment and investments in different economic sectors in both West and East Germany. In the following sections, we describe these two main data sources in more detail and provide information on additional complementary datasets.

3.1 SIRA Data

Our main data on the Stasi's industrial espionage activities are taken directly from SIRA's Sub-Database 11 (*Teildatenbank 11*), which essentially comprises records of all scientific-technical information that the Stasi's informants in the West passed on to the HVA between 1968 and 1989.[7] In total, 189,725 pieces of information were recorded over this time period, corresponding to an annual average inflow of 8,624 items. Figure 1 displays the distribution of this flow of information over time. We omit from our analysis the early years 1968 and 1969, as well as the final year 1989, since these are only partially covered by the SIRA data. The figure shows that the annual inflow of information was initially on a declining trend but that this trend reversed in 1979, after which the inflows increased steadily, eventually peaking in 1988, the last year prior to the fall of the Berlin wall, with a record of 15,658 pieces of information.[8]

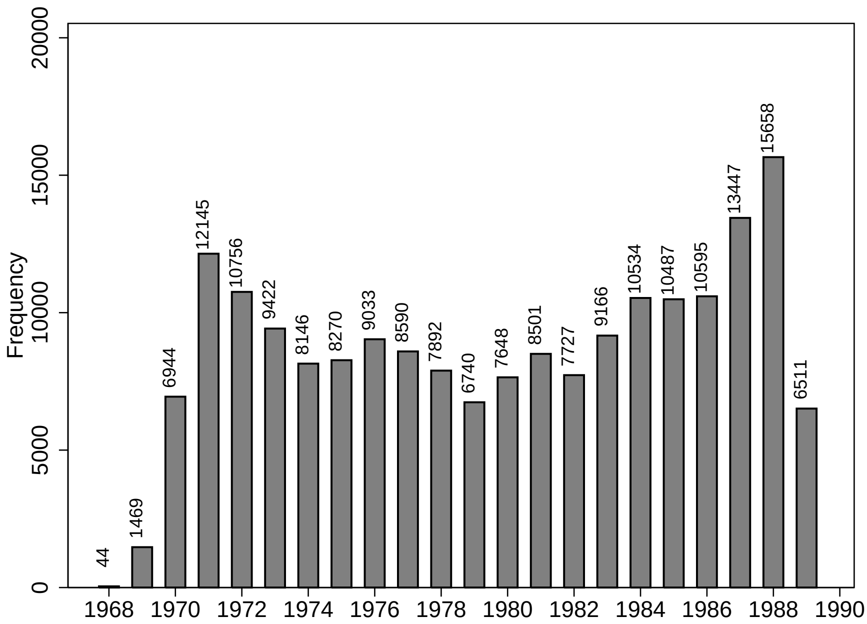
Upon arrival at the Stasi, specialist internal evaluators created, for each incoming piece of information, an electronic entry in the SIRA database in which they recorded, among other things, the date of arrival of the information, the source of the information as well as a number of – often highly specific –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 and/or East German research facilities, for further assessment and economic exploitation. In total, the Sub-Database 11 comprises 143,005 distinct keywords, 68.5% of which are only used once throughout the entire 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 95th percentile of 10 and a maximum of 145 keywords.

To operationalize these keywords and connect them to our sectoral time series data, we selected in a first step the 2,000 most frequently occurring keywords, which together account for 63.8% of

[7] 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 eventually went online in July 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.

[8] 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% 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.

Figure 1: Information Inflow, 1968-1989



Note: Figure shows the annual inflow of information received by the HVA between 1968 and 1989. Data for 1968/69 and 1989 incomplete.

all keyword entries in the database, and assigned them to their corresponding sectors. Table A-1 in the appendix 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% of the 2,000 most common keywords to at least one of the 16 sectors for which we have information on output, employment, and investments.[9] 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% are not described by any sector-specific keyword.

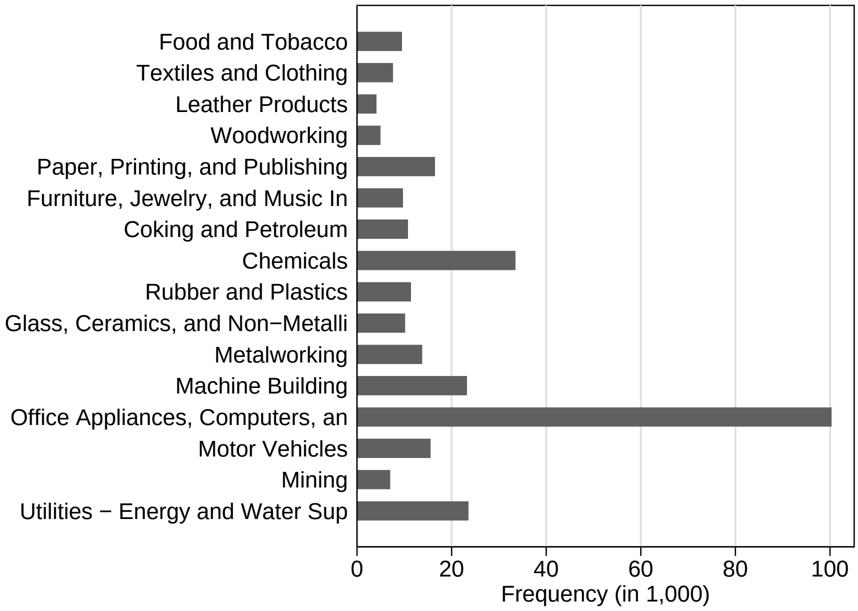
Figure 2 shows the sectoral distribution of the 151,627 pieces of information that could be allocated to at least one of the 16 available sectors over the period 1968 to 1989. In our baseline specification, we count a piece of information as pertaining to a specific sector if it is described by at least one keyword corresponding to that sector. A given information may therefore pertain to more than one sector.[10] 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).

Looking at the providers of these pieces of information, the SIRA database identifies 2,968 distinct informants based on their assigned registration numbers. Table A-2 in the appendix

[9] The remaining 45% are either not classifiable (80.9%) 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%). Note that a given keyword can relate to more than one sector.

[10] As a robustness check, we use a weighted inflow measure by assigning each piece of information to the relevant sectors in proportion to the number of sector-specific keywords describing it. As an additional alternative, we also assign pieces of information to individual sectors using modern machine learning tools. More details are provided in Section 5.2.

Figure 2: Sectoral Distribution of Information



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

lists the 20 most productive sources of information over the period 1968 to 1989. Informant "FROEBEL" with registration number XV/6603/80, who worked at the East German embassy in Washington, was the top source in terms of quantity, delivering 5,344 distinct pieces of information, with the first piece received in 1982 and the last in 1989. His overall reliability was assessed with the highest possible value "A", which meant "reliable" and which was awarded in 66.1% of all cases (29.7% of informants were assessed as "trustworthy" and 4.2% as "not checked"). However, these top-ranking informants were certainly an exceptional group in terms of the amount of information they generated. Across the entire 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 Figure A-1 in the appendix. 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. Figure A-2 in the appendix 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 an ongoing process, with increased efforts from the mid-1980s onwards. The right panel shows that, for reason we cannot ascertain, informants also continuously ceased to provide further information. We will exploit this fact later on in the construction of one of our instrumental variables.

3.2 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 (2013). The purpose of this publication was to provide a comparable, retroactive 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, with a market-based economy in West Germany pitted against a centrally-planned economy in East Germany, such computations constitute a challenging task, not least because West and East Germany followed different national accounting standards throughout the pre-unification period.[11]

The historical 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 1991 and whose mission included, besides the collection, protection and documentation of the existing statistical data in the former GDR, the retroactive computation of key economic indicators based on current methodological concepts and taxonomies (Lachnit, 1993). In 2000, this work led to a first publication 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.[12]

In a series of subsequent publications, Heske (2005, 2009, 2013) builds on these initial findings but makes four important additional contributions. First, he translates all values of output and investment in the GDR into constant East German Mark with respect to the base year 1985, taking account of the complex issues arising from the qualitative upgrading of existing products and introduction of new products.[13] Second, he converts all values into constant 1995 euros, thus allowing a direct comparison between the economic performance of West and East Germany over time. A key advantage in this process is the fact that many of the goods produced in the former GDR were observed both priced in East German Mark and, after the monetary union on 1 July 1990, in West German Deutsche Mark, allowing the computation of differentiated sector-specific conversion coefficients. Third, Heske extends the time horizon to the earlier period 1950 to 1969, for which the existing data basis, however, is significantly more limited. Finally, and crucially for our analysis, he constructs separate time series for different economic sectors. The depth of the sectoral differentiation is thereby governed by data availability, allowing in the end a distinction of three broad industry sectors – mining, energy and water, and manufacturing – and, within manufacturing, a further differentiation of 14 sub-sectors.

Figure A-3 in the appendix shows time series for log gross value added per worker in West and East Germany by sector between 1970 and 1989. Apart from the energy and water sector, the productivity of workers in West Germany exceeds that of workers in East Germany, in many sectors, including some of the biggest ones such as *Metalworking* and *Office Appliances, Computers, and Electronics*, by a substantial amount (1.89 and 1.96 log points, respectively, on average over the time period considered). For comparison, we also add the corresponding time series for West Germany from the EU KLEMS Growth and Productivity Accounts. Apart from the *Coking and Petroleum* sector, where the EU KLEMS data show significantly higher productivity levels than the Heske data, there is a high level of agreement between the two data sources, both in terms of

[11] 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). Only after unification in 1990, the two systems were harmonized by introducing the SNA system on the territories of the former GDR.

[12] Statistisches Bundesamt: Sonderreihe mit Beiträgen für das Gebiet der ehemaligen DDR, Heft 33, Wiesbaden 2000.

[13] A key characteristic of the price formation mechanism in the centrally-planned economy of the former GDR was the existence of significant differences between the prices set at the production stage, and the prices set at the final consumption stage. While producer prices (*Industrieabgabepreise*) were periodically adjusted to reflect changes in the costs of production, consumer prices were predominantly set with a view to political and social conditions.

levels and dynamic patterns over time.

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 subject of extensive and controversial discussions (see e.g. Statistisches Bundesamt, 1999). In the context of our study, it is therefore important to emphasize that the sector-specific time series data we use 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. Overall, we are therefore confident that these data provide an overall good reflection of the key economic developments in West and East Germany over the time period considered.[14]

3.3 Patent and Trade Data

To isolate the impact of industrial espionage on productivity, it is important to control for other key 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 over our observation window 1970 to 1989. To proxy for both countries' own R&D activities, we therefore use the annual number of sector-specific patent applications, scaled by industry output.[15] For West Germany, we obtain these from the DEPATISnet database of the German Patent Office and the EPAB database of the European Patent Office. From these online databases, we extracted the annual number of West German patent applications for each IPC category between 1970 and 1989 and then summed up the number of applications across all IPC's belonging to one of our 16 industry sectors.[16] In cases in which a given IPC pertained to more than one industry sector, we assigned fractions of the corresponding numbers of patents to each industry using weights taken from the MERIT concordance table IPC - ISIC (rev. 2).

The source of our East German patent data consist of formerly confidential publications summarizing the annual innovation activities in the GDR (*Ergebnisse der Erfindertätigkeit und Schutzrechtsarbeit*) for the period 1970 to 1989, published by the East German Statistical Office (SZS). For each year and state combine, these publications report a number of innovation-related outcomes, including the number of patent applications.[17] To construct sector-specific outcomes,

[14] Two important studies by the Deutsches Institut für Wirtschaftsforschung (DIW, 1987) and the Federal Statistical Office (Hölder, 1992) reach a similar conclusion regarding the reliability of the statistical information in the former GDR.

[15] See Lach (1995) for a related study estimating the productivity returns to patents as a proxy for R&D, and Hall, Jaffe and Trajtenberg (2005) for estimates of the market value returns to patents.

[16] The European Patent Office has accepted patent applications for its member states since 1978. The overall 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.

[17] The other innovation outcomes provided are the number of patent applications from R&D activities (1970-1982), the number of innovators applying for patents (1980-1982), the number of patent engineers working in the patent office (*Büro für Schutzrechte*) (1980-1989), and the number of university cadres working in R&D (1986-1989). While we cannot use these alternative measures due to their restricted time coverage, their correlation with the number of patent applications is very high, 0.998 with respect to the number of patent applications from R&D activities, 0.978 with respect to the number of innovators applying for patents, 0.971 with respect to the number of patent engineers, and 0.976 with respect to the number of university cadres working in R&D. For an overview of the patent law in the former GDR and its development in the post-war period, see Wiessner (2013).

we assign each state combine to one of our 16 industry sectors, which is straightforward given that combines were organized along sectoral lines, and sum the number of patent applications across combines operating in the same sector. Figure A-4 in the appendix shows the number of patent applications by sector in West and East Germany for the period 1970 to 1989.

Finally, we use trade data from the "World Trade Flows 1962-2000" collected by Feenstra, Lipsey, Deng, Ma and Mo (2005) to source imports data for West and East Germany.[18] We convert the SITC revision 2 format of the trade data to the ISIC2 system of our industry data using the concordance constructed by Muendler (2009). Following Cameron et al. (2005), we construct a sector-specific measure of the relative import intensity between West and East Germany, defined as the difference in the West and East German ratios of sector-specific imports from the whole world divided by output.

4 Empirical Framework

4.1 Main Specification

In this section, we present our empirical framework. In each industry j of country i, either West Germany (W) or East Germany (E), output Y^i_{jt} in period t is produced using physical capital K^i_{jt} and labor L^i_{jt} according to a standard neoclassical production function, $Y^i_{jt} = A^i_{jt}F(K^i_{jt}, L^i_{jt})$, where A^i_{jt} denotes total factor productivity (TFP) and F is assumed to be homogeneous of degree one. We assume that TFP is not just a function of the R&D knowledge stock, G^i_{jt}, but also of the stock of knowledge accruing from espionage activities, E^i_{jt}. In the spirit of the empirical literature on R&D and productivity growth (e.g. Griffith et al., 2004, Buccirossi, Ciari, Duso, Spagnolo and Vitale, 2013), after taking logarithms and differencing with respect to time, the rate of sector-specific TFP growth is given by

$$\Delta \ln A^i_{j,t+1} = \alpha + \beta^i \Delta \ln E^i_{jt} + \gamma^i \Delta \ln G^i_{jt} + \theta^i \ln \left(A^F_{jt}/A^i_{jt} \right) + \mathrm{X}'^i_{jt}\Phi^{\mathrm{i}} + \lambda^i_j + \pi^i_t + \mu_{jt} + \varepsilon^i_{jt} \qquad (1)$$

where $\ln(A^F_{jt}/A^i_{jt})$ measures a country's distance to the world technological frontier A^F_{jt}, X^i_{jt} is a vector of country-specific control variables, λ^i_j are country-sector fixed effects, π^i_t are country-time fixed effects, and μ_{jt} are world-sector-time fixed effects. The parameters γ^i and β^i are the elasticities of output with respect to the R&D knowledge stock and the knowledge stock acquired through industrial espionage, respectively.[19] Assuming negligible rates of depreciation of both types of knowledge, the speed of technological progress in a country can be expressed as

$$\Delta \ln A^i_{j,t+1} = \alpha + \rho^i \left(\frac{S^i_{jt}}{Y^i_{jt}} \right) + \eta^i \left(\frac{R^i_{jt}}{Y^i_{jt}} \right) + \theta^i \ln \left(\frac{A^F_{jt}}{A^i_{jt}} \right) + \mathbf{X}'^i_{jt}\mathbf{\Phi}^{\mathrm{i}} + \lambda^i_j + \pi^i_t + \mu_{jt} + \varepsilon^i_{jt},$$

where $S^i_{jt} = \Delta E^i_{jt}$ is the inflow of sector-specific information acquired through industrial espionage and $R^i_{jt} = \Delta G^i_{jt}$ is a measure of sector-specific R&D investments, implying that ρ^i is the rate of return to industrial espionage $(dY^i_{j,t+1}/dE^i_{jt})$ and η^i the rate of return to R&D $(dY^i_{j,t+1}/dG^i_{jt})$.

Our main outcome of interest is the gap in the TFP growth rate between the two parts of Germany which, from the perspective of East Germany, can we viewed as the change in the

[18] The dataset is available at the UC Davis Center for International Data `http://cid.econ.ucdavis.edu/wix.html`.

[19] Thus $\beta^i = (dY^i_{j,t+1}/dE^i_{jt})(E^i_{j,t-1}/Y^i_{jt})$ and $\gamma^i = (dY^i_{j,t+1}/dG^i_{jt})(G^i_{j,t-1}/Y^i_{jt})$.

distance to the technological frontier in West Germany. Taking differences between West and East Germany's TFP growth rates and defining $\lambda_j \equiv \lambda_j^W - \lambda_j^E$, $\pi_t \equiv \pi_t^W - \pi_t^E$, $\mathbf{X}_{jt} \equiv \mathbf{X}_{jt}^W - \mathbf{X}_{jt}^E$ and $\varepsilon_{jt} \equiv \varepsilon_{jt}^W - \varepsilon_{jt}^E$ leads to our main estimation equation

$$\Delta \ln \left(\frac{A_{jt+s}^W}{A_{jt+s}^E}\right) = \rho \left(\frac{S_{jt}^E}{Y_{jt}^E}\right) + \eta \left(\frac{R_{jt}^W}{Y_{jt}^W} - \frac{R_{jt}^E}{Y_{jt}^E}\right) - \theta \ln \left(\frac{A_{jt}^W}{A_{jt}^E}\right) + \mathbf{X}_{jt}'\mathbf{\Phi} + \lambda_j + \pi_t + \varepsilon_{jt}, \tag{2}$$

where $\rho = -\rho^E$ and where we initially assume that the marginal effects of R&D investments, the distance to the world technological frontier and the control variables on TFP in West and East Germany are the same ($\eta^W = \eta^E = \eta, \theta^W = \theta^E = \theta$, and $\Phi^{\mathrm{W}} = \Phi^{\mathrm{E}} = \Phi$).[20] The vector of sector-specific fixed effects λ_j in equation (2) captures differential sector-specific unobserved heterogeneity in TFP growth in West and East Germany.[21] The vector of time fixed effects π_t allows for differential technological advances on the country level that affect all sectors in the same way. By taking differences between West and East German TFP growth, we also implicitly control for all time-varying sector-specific TFP shocks μ_{jt} that affect West and East Germany in the same way.

Note that equation (2) does not include a term for West German industrial espionage S_{jt}^W which is unobserved and would thus be part of the error term. Although 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 scale of West German industrial espionage. Since East Germany's industrial espionage was to such a large extent driven by trade embargoes which West Germany did not suffer from, the relative return to industrial espionage compared to standard R&D ought to have been rather low in West Germany. Moreover, assuming that the returns to industrial espionage in both countries are positive, and that industry-level espionage is positively correlated in the two countries, the omission of West German espionage activities, by way of the standard omitted variable bias formula (Angrist and Pischke, 2009) would lead to an understatement of the effect of East German industrial espionage on the productivity gap in equation (2).[22]

The identifying assumption in estimating equation (2) 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 $\varepsilon_{jt}(= \varepsilon_{jt}^W - \varepsilon_{jt}^E)$. There are a number of potential threats to this assumption. First, assuming a constant espionage intensity, 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_{jt}^W, which in turn would lead to an upward bias of our parameter of interest ρ. In this case, our findings would constitute a lower bound of the true effect of industrial espionage on relative TFP growth. The second threat arises 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 particularly fast with the West. 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

[20] We relax these assumptions in Section 5.6.

[21] Note that the time dimension of our industry panel is relatively long, so that the bias of the coefficients of weakly exogenous variables in equation (2) arising from the inclusion of country-sector fixed effects is likely to be small (see Nickell, 1981).

[22] Of course, West German counterintelligence measures were an important tool to prevent unwanted technology transfers from the West to the East, but these measures are likely to have reduced S_{jt}^E directly.

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 from espionage. 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 the relative productivity growth between West and East Germany. In addition, 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.

Before estimating equation (2), we need to determine the time intervals over which to construct the sector-specific 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 the arrival of new information about West German technology would be translated into measurable changes in East German productivity within a single year. Our main specification will therefore relate changes in log TFP gaps over a three-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.[23] To exploit the available data as efficiently as possible, and to 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 (compare Harri and Brorsen, 2009). We present both conventional standard errors clustered at the sectoral level and p-values calculated using the wild cluster bootstrap-t method proposed by Cameron, Gelbach and Miller (2008), which represents an important inference improvement when the number of clusters, as in our case, is relatively low. We weight observations by the average number of workers in the corresponding sector over the sample period. For robustness, we also present results using non-overlapping observations and specifications in which observations are either unweighted or weighted by the average output in each sector.

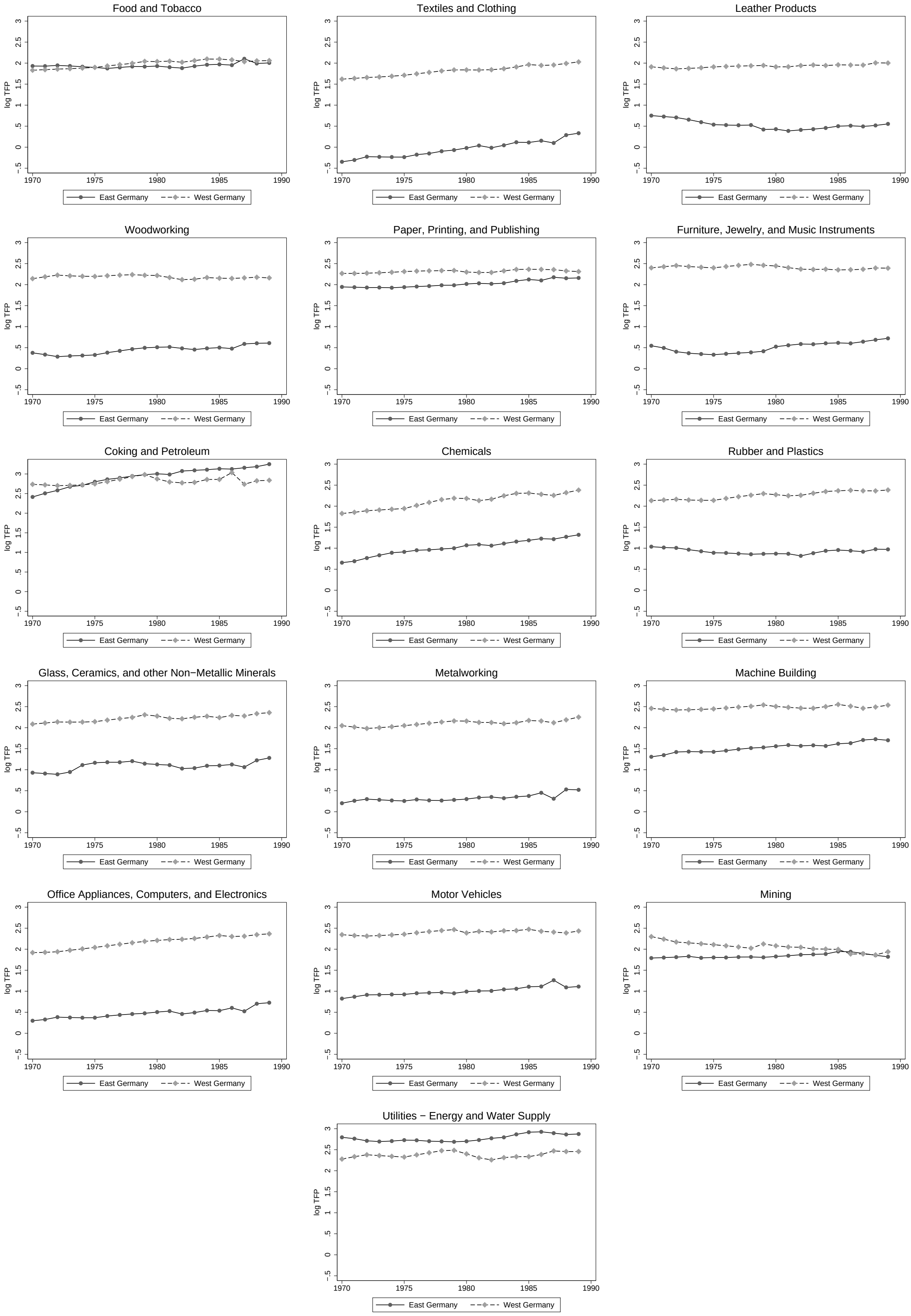
4.2 Obtaining Estimates of TFP

As there are no direct measures of TFP available for the time period considered, we use our industry-level data to back out measures of sector-specific TFP by means of a standard growth accounting exercise (Mankiw et al., 1992; Caselli, 2005; Caselli and Coleman, 2006). As a starting point, we assume that the production function in each sector is Cobb-Douglas, so that $Y^i_{jt} = A^i_{jt}(K^i_{jt})^{\alpha}(L^i_{jt})^{1-\alpha}$. Transforming outputs and inputs into per worker terms, taking logs, differencing over time and rearranging leads to

$$\Delta \ln A^i_{jt} = \Delta \ln y^i_{jt} - \alpha \Delta \ln k^i_{jt} \tag{3}$$

[23] Results based on annual observations are consistent with our main findings and highly significant, but smaller in magnitude (see Table A-5).

Figure 3: Log Total Factor Productivity by Sector



Note: The individual panels depict the estimated log TFP by sector for West and East Germany over the period 1970 to 1989. TFP measures are constructed using the perpetual inventory method as described in the text, assuming an annual depreciation rate of the capital stock of 6% and a capital share of output of 33% in each sector.

where y^i_{jt} and k^i_{jt} denote output per worker and the capital-labor ratio, respectively.[24] 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 (3) 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 sector-specific 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 in the data (1950), and g_j the sector-specific average geometric growth rate for 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 δ to 0.06 for all sectors 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 parameter α corresponds to the capital share. Following again the literature, we set this share equal to 0.33 in equation (3) and then use the relative changes in output per worker and in the capital-labor ratios to back out estimates of technological progress, $\widehat{\Delta \ln A^W_{jt}}$ and $\widehat{\Delta \ln A^E_{jt}}$, which we then plug into our main estimation equation (2).[25] Figure 3 displays the estimated log TFP profiles for each of our 16 sectors between 1970 and 1989. Apart from the *Food and Tobacco*, *Coking and Petroleum*, and the *Utilities* sectors, West Germany's total factor productivity always 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 in log TFP between West and East Germany are somewhat sensitive to the sector-specific capital shares used in the calibration and the conversion of East German Mark into West German Deutsche Mark (and euros) in the industry-level data, they do not affect the estimation of our parameters of interest since we are looking at the effect of industrial espionage on *changes* in log TFP. 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 on sector-level capital shares or depreciation rates.

Table 1 provides an overview of all variables used in our main empirical specification. The main regressor of interest is the inflow of information scaled by sector-specific output. Over the time 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 3-year change in log TFP amounted to 2.5% in West Germany and 4.6% in East Germany. Output per worker grew somewhat faster, 5.0% on average in West and 9.0% in East Germany.[26] The

[24]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) show that skills between East and West were actually 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.

[25]We check the sensitivity of our results to different values of the assumed capital share and depreciation rate in Table A-7. As a further robustness check, we also use West German sector-specific capital shares taken from the EU KLEMS data in the calculation of the TFP growth rates (see column 7 of Table 3).

[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 1: Summary Statistics

	West Germany		East Germany		Difference	
	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
Inflow/Y			1.524	(1.403)		
Δ Log TFP	0.025	(0.072)	0.046	(0.070)	-0.020	(0.096)
Δ Log 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	2.227	(0.250)	1.194	(0.866)	1.033	(0.752)
Log Output per Worker	3.679	(0.414)	2.385	(1.091)	1.294	(0.782)
Imports/Y	2.412	(4.564)	0.296	(0.340)	2.116	(4.584)

Note: Summary statistics computed for 3-year overlapping observations for the period 1970 to 1989. 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).

number of patent applications per 1 million euros of output was broadly comparable in West and East Germany, 0.392 in the West and 0.313 in the East. 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 1.033 and 1.294, respectively, implying a 181% higher TFP and a 265% higher output per worker in West Germany than in East Germany. 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 East Germany and its resulting difficulties in trading with the rest of the world. Table A-3 in the appendix reports corresponding summary statistics separately for each sector and is complemented by Figures A-5 and A-6 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.

5 Results

5.1 Main Results

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 (2). 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 significant effect of industrial espionage on the log TFP gap with a point estimate of -0.039. In column (2), we add the gap in the number of patent applications per 1 million euros of output between West and East Germany as a proxy for sector-specific R&D investments as an additional control variable. The inclusion of this control variable may help 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 by means of covert operations in West Germany. Not controlling for East German R&D activities would thus lead to a downward bias in our parameter of interest. On the other hand, more R&D activities in West Germany

Table 2: Industrial Espionage and Productivity

	Log TFP			Log Output per Worker		
	Baseline spec	Patents gap	Lagged gap	Baseline spec	Patents gap	Lagged gap
	(1)	(2)	(3)	(4)	(5)	(6)
Inflow/Y	-0.039*	-0.046**	-0.049***	-0.030*	-0.040**	-0.039**
	(0.020)	(0.020)	(0.013)	(0.016)	(0.018)	(0.017)
Patents/Y Gap		0.071**	-0.024		0.103***	0.012
		(0.028)	(0.022)		(0.026)	(0.028)
Log TFP Gap			-0.589***			
			(0.097)			
Log Output/Worker Gap						-0.514***
						(0.100)
P-value WB	0.068	0.042	0.010	0.080	0.082	0.116
R-squared	0.31	0.33	0.55	0.31	0.35	0.51
Observations	240	240	240	240	240	240

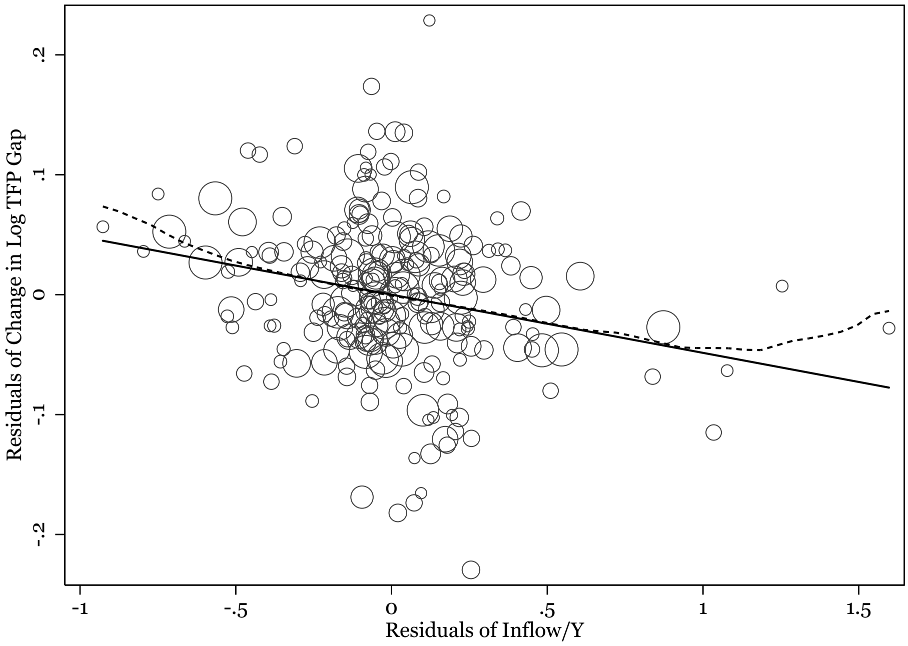
Note: Sample based on 3-year intervals and overlapping observations for the period 1970 to 1989. All regressions include time- and sector-specific fixed effects. Observations are weighted by the average number of workers in a sector. The dependent variable is the change in the log TFP gap between West 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 clustered at the sectoral level in parentheses. P-value WB denotes p-values, relating to the Inflow/Y estimate, from Cameron et al. (2008) clustered wild bootstraps using 1,000 replications.

could mean that there is more available information around that could be siphoned off by East German informants. In this case, not controlling for West German R&D activities would give rise to an upward bias in our parameter of interest. As column (2) reveals, the latter effect dominates: controlling for the patent gap between West and East Germany reduces our main parameter of interest to -0.046. The coefficient of the patent gap control variable itself is positive, indicating, as expected, a positive role for own R&D activities on future TFP growth. Column (3) represents our preferred specification, where we add the initial log TFP gap as a further control variable. This leads to a small additional decrease of our main parameter of interest to -0.049, which is highly significant based on both the conventional cluster-robust standard errors reported in parentheses and p-values from Cameron et al. (2008)'s wild bootstrap-t clustering. The estimated coefficient suggests an economically meaningful effect of industrial espionage on productivity growth, with a one standard deviation increase of 1.4 in the information flow per 1 million euros of output reducing the gap in log TFP between West and East Germany by 6.9 percentage points. Note that the coefficient of the initial log TFP gap, multiplied by minus one, 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 thus find evidence for technology transfer as a source of productivity growth for countries behind the technological frontier.

Figure 4 visualizes the negative relationship between industrial espionage and changes in the log TFP gap between West and East Germany by plotting their residualized values corresponding to our preferred specification in column (3) of Table 2. Importantly, this relationship is not driven by any particular outliers in the data and, over a large range of the inflow variable's support, well approximated by a linear function.

The right panel of Table 2 shows the corresponding results for the change in the log output per

Figure 4: Industrial Espionage and Productivity



Note: 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 linear local polynomial estimator.

worker gap between West and East Germany. The results closely mirror those for the log TFP gap, which is consistent with a narrowing productivity gap driving a narrowing output per worker gap between West and East Germany.[27] Table A-4 in the appendix reports 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 significant and comparable in magnitude to their counterparts in Table 2.

5.2 Robustness Checks

In Table 3, we perform a number of robustness checks for our main 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 corresponding results for output per worker in Table A-6 of the appendix. 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 the parameter on the inflow variable by more than half to -0.076. In contrast, not weighting at all leaves the estimated effect almost unaffected as shown in column (3). In column (4), we exclude all observations pertaining to the sector *Office Appliances, Computers and Electronics*, which was of particular interest to the East German government and which comprises by far the biggest share of the overall information received (compare Figure 2). Excluding this important sector leads to only a small decrease in the estimated impact of industrial espionage on log TFP gaps, from -0.049 to -0.043. In column (5), we

[27] Note from equation (3) that the coefficient from this regression, ρ_y, is equal to the sum of the corresponding coefficient from the log TFP specification and the scaled coefficient from a specification where the dependent variable is the relative change in the sector-specific capital-labor ratio, $\rho_A + \alpha\rho_k$. Since $\rho_y = -0.039$ and $\rho_A = -0.049$ in our preferred specifications, the effect of industrial espionage on the relative growth in capital intensity is thus $\rho_k = 0.030$.

Table 3: Robustness - Log TFP

	Main spec	Weighted by output	No weights	No IT	Sector trends	Trade gap	Flexible capital shares	Keyword weighted	Machine learning
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Inflow/Y	-0.049***	-0.076**	-0.047***	-0.043**	-0.043***	-0.047***	-0.044***	-0.086***	-0.046**
	(0.013)	(0.032)	(0.014)	(0.017)	(0.012)	(0.013)	(0.013)	(0.024)	(0.018)
Patents/Y Gap	-0.024	-0.022	0.002	0.022	0.013	-0.019	-0.020	-0.017	-0.023
	(0.022)	(0.044)	(0.032)	(0.045)	(0.076)	(0.023)	(0.025)	(0.020)	(0.017)
Log TFP Gap	-0.589***	-0.783***	-0.565***	-0.595***	-1.201***	-0.592***	-0.574***	-0.606***	-0.602***
	(0.097)	(0.172)	(0.091)	(0.095)	(0.095)	(0.102)	(0.107)	(0.087)	(0.087)
Imports/Y Gap						-0.001			
						(0.003)			
P-value WB	0.010	0.044	0.044	0.060	0.008	0.014	0.012	0.003	0.044
R-squared	0.55	0.58	0.54	0.54	0.70	0.55	0.54	0.55	0.53
Observations	240	240	240	225	240	234	240	240	240

Note: 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 (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 construct our TFP measures using sector-specific capital shares. In column (8), we weight each piece of information according to the number of categorized keywords assigned to each sector. In column (9), we use machine learning methods to assign pieces of information to industry sectors. Standard errors clustered at the sectoral level in parentheses. P-value WB denotes p-values, relating to the Inflow/Y estimate, from Cameron et al. (2008) clustered wild bootstraps using 1,000 replications.

add sector-specific linear time trends to our specification, which effectively allow for accelerating or decelerating relative productivity growth in different sectors. Once again, this has little impact on our parameter of interest. 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 a control variable in column (6) with little effect.[28] In column (7), we construct our TFP measures using average sector-specific capital shares over the period 1970 to 1989 taken from the EU KLEMS Growth and Productivity Accounts. Once again, our main parameter of interest remains relatively 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 (8), we assign each piece of information to the relevant sector(s) 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 mea-

[28] Note that while the point estimate of the import gap variable is close to zero and not significant in the reported specification, if one excludes the initial log TFP gap, it increases to a highly significant 0.011 (0.003), suggesting a productivity-enhancing role of international trade. In unreported specifications, we also included, in addition to the general import gap variable, interactions of industry dummies with the West-East difference in a) the share of high-technology imports in total imports and b) the fraction of high-technology imports imported from CoCom countries (Australia, Belgium, Canada, Denmark, France, Germany, Greece, Italy, Japan, Luxembourg, Netherlands, Norway, Portugal, Spain, Turkey, the United Kingdom and the United States) in our estimation equation. These interactions serve as additional controls for potential technology transfers through trade by allowing East (relative to West) Germany's ability to import advanced technologies to have a differential effect on different industries over time. The inclusion of these additional trade controls, however, has little impact on our main parameter of interest, with a point estimate of -0.049 (0.029).

sure of information inflows increases the estimated impact of industrial espionage on the change in the log TFP gap between West and East Germany substantially, from -0.049 to -0.086. Our results based on the unweighted inflows can thus be interpreted as a lower bound of the effect of industrial espionage on relative productivity growth. Apart from the weighting issue, another potential problems of mapping pieces of information to different sectors on the basis of the 2,000 most frequently occurring keywords is that a non-negligible fraction of 18.6% of the total pieces of information received by the Stasi cannot be assigned to a sector since they are not described by any of the allocated keywords (see Section 3). Furthermore, by focusing on a limited set of frequently occurring keywords, we might ignore valuable information embedded in the remaining, more rarely occurring keywords. To deal with this issue, we use modern machine learning tools building on Cortes and Vapnik (1995) to systematically assign *all* pieces of information to individual sectors on the basis of the *universe* of keywords recorded in the data.[29] As shown in column (9) of Table 3, this more sophisticated approach yields very similar point estimates as our initial more ad hoc 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 in many cases there are only 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.

In the appendix, we provide a number of further robustness checks. In Table A-5, we vary the length of the time interval over which we measure 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 change in the log TFP gap between West and East Germany based on annual variation is muted relative to our main findings. When we use 5-year intervals, the point estimates are broadly similar but in several cases no longer statistically significant due to the smaller sample sizes. Table A-6 reports corresponding robustness checks when using output per worker as our productivity measure. Finally, in Table A-7, we show that our main results are robust to different calibrations of the sector-level capital shares and depreciation rates in the process of backing out sector-specific TFP measures.

5.3 Instrumental Variables

One potential concern with our analysis thus far is that the results could 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 productivity-enhancing innovations in West Germany widens the productivity gap to the East while at the same

[29] 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%. To test the performance of the algorithm on the unlabeled dataset, we train the algorithm on 80% of the labeled observations and test its performance on the remaining 20%, achieving an accuracy in this hold-out exercise of 71%.

time increasing the inflow of espionage information even in the absence of any strategic behaviour on behalf of the Stasi and its informants. This is because, at constant espionage intensity, if 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, our inflow measure would be positively correlated with the error term ε_{jt}^{W} in equation 2, upward biasing our estimate of the impact of industrial espionage on the productivity gap between West and East Germany. Apart from 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 be downward biased, or technologically fall behind in the future, in which case our estimate would be upward biased.

By exploiting variation around sector-specific linear time trends in relative productivity growth, which are absorbed by the vector of λ_j's, 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.[30]

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 different sectors at the time are exogenous to any subsequent changes in 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 scaled 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 this inflow to be related to different industries in terms of content 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 4 show the first-stage results from the instrumental variable estimation for the change in the log TFP gap and the log 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 60.7 and 59.9, respectively. As reported in columns (2) and (6), the 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 industries in which East Germany was correctly anticipated to fall behind. A Hausman test, however, shows that the differences between the OLS and IV estimates are not statistically significant.

[30] Reshuffling existing informants across sectors was difficult since most informants had specific technical training and were gathering information under the cover of a long-term career in specifically targeted West German companies.

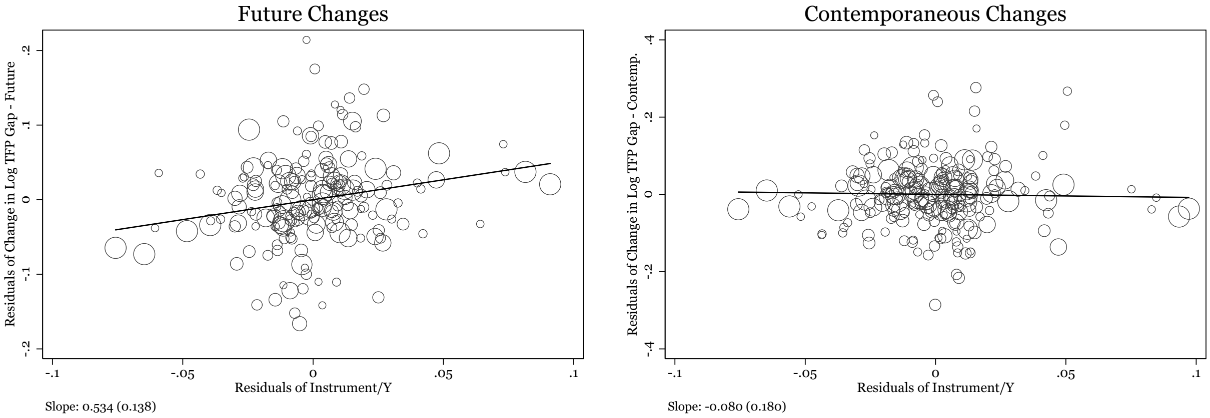
Table 4: Instrumental Variables

	Log TFP				Log Output per Worker			
	Old Informants		Exit of Informants		Old Informants		Exit of Informants	
	First stage	IV results	First stage	IV results	First stage	IV results	First stage	IV results
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inflow/Y		-0.066***		-0.121***		-0.059**		-0.119***
		(0.025)		(0.035)		(0.028)		(0.040)
Patents/Y Gap	-0.548	-0.020	-0.013	-0.043	-0.531	0.018	0.017	0.001
	(0.391)	(0.022)	(0.222)	(0.048)	(0.388)	(0.025)	(0.196)	(0.049)
Log TFP Gap	0.197	-0.591***	0.654	-0.701***				
	(0.427)	(0.095)	(0.568)	(0.147)				
Log Output/Worker Gap					0.298	-0.514***	0.844**	-0.613***
					(0.305)	(0.096)	(0.383)	(0.133)
Instrument Old Informants	0.637***				0.640***			
	(0.082)				(0.083)			
Instrument Exits			-4.409***				-4.568***	
			(0.607)				(0.536)	
F-stat		60.7		52.7		59.9		72.6
Observations	240	240	192	192	240	240	192	192

Note: 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 $\left(\sum_{i\in 1970}\theta_{i,70}\lambda_{ij,70}\sum_{s=t-2}^{t} I_s\right)/Y_{jt}^{E}$, where $\theta_{i,70}$ is the share of the total information received in 1970 that was 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 $\left(\sum_{s=t-5}^{t-3}\sum_{i^*(s)|\bar{I}_{i^*j}\geq 20}\bar{I}_{i^*j}\right)/Y_{jt}^{E}$, 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.

In our second IV approach, we exploit the fact that a number of informants who used to provide a steady stream of information in the past at some point suddenly ceased to deliver any further information. This could be because these informants 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 scaled hypothetical inflow that would have been expected to arrive at the Stasi from informants who exited in the previous 3-year period had they 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 period s (compare the right panel of Figure A-2). The more informants exit during a given time period and the more prolific they were in the past in generating information for the Stasi, 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 because their

Figure 5: Exits of Informants and Changes in the Log TFP Gap



Note: 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 the left panel and the end of t-6 and t-3 in the right panel. 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.

permanent exits are particularly likely to be exogenous to the Stasi's strategic objectives.[31]

While arguably exogenous from the East German perspective, one potential concern with this instrument is 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 particularly fast technological progress. In this case, some of the exits used in the construction of the instrument would be endogenous, leading to a downward bias and therefore overstatement of the impact of industrial espionage on relative TFP growth. There is no historical evidence that would point towards such strategic counterintelligence responses on the sectoral level by West German authorities. Considering the extent of East Germany's infiltration of the West German economy, the actual exposure of informants engaged in industrial espionage was very limited, so that arguably the vast majority of observed exits of informants were driven by other unrelated factors such as job loss or retirement.

Figure 5 provides some suggestive evidence for this claim. In the left panel, 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.[32] The relationship is positive with a highly significant point estimate of 0.534, 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 the right panel, we use the same empirical specification but now look at 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 -0.080 shows that exits of prolific 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 policy of the Stasi to deactivate its informants in slow-moving sectors.

[31] As a robustness check, we use alternative thresholds of 10 and 50 pieces of information, leading to very similar estimates. In addition, we also use a simple count of the number of exits of prolific informants as an instrument, conditional on satisfying the imposed productivity thresholds, which again yields similar results.

[32] Figure A-7 in the appendix shows the corresponding evidence for changes in the log output per worker gap.

Columns (3) and (7) of Table 4 report the first stage results corresponding to the reduced form relationships illustrated in the left panels of Figures 5 and A-7, 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 two, which would be consistent with an intensification of industrial espionage in sectors in which the productivity gap to West Germany was widening, but also with a potential downward bias of the IV estimates due to a remaining partial endogeneity of the instrument.[33] Because of this possibility and because the differences between OLS and IV estimates are once again not statistically significant, we continue to focus on our more conservative OLS specification in the remaining sections of the paper.[34]

5.4 Placebo Estimation

Before turning to our heterogeneity analysis, we perform a type of placebo estimation in which we relate our measure of East German espionage intensity to the relative growth rates in productivity between West Germany and a set of other developed countries of the West. Since East Germany did not share information with these countries during the Cold War period, the information it received from its informants in the West should not have impacted those countries' productivity growth relative to that in West Germany. If, however, our measure of information inflow was mechanically linked to the extent of productivity-enhancing activities in West Germany, attenuating our estimated effects, we would expect it to be positively correlated with the change in the productivity gap between West Germany and other countries.

Table 5 shows the results from the placebo estimations for all 18 countries for which the EU KLEMS Growth and Productivity Accounts provide the relevant information on sector-level output per worker for the period 1970 to 1989. The dependent variable is the change in the log output per worker gap between West Germany and the country listed in the respective column heading. We follow the same specification as in column (6) of Table 2 but do not include a proxy for overt R&D activities since data on patents and R&D investments are sketchy in the EU KLEMS data for the time period considered. Column (1) of Table 5 shows the results for this particular specification of our baseline model for West and East Germany. Columns (3) to (20) show the corresponding results for the other countries. All estimates of our parameter of interest are statistically insignificant and in most cases also considerably smaller in magnitude than the benchmark estimate in column (1). The only exception is the estimate for Luxembourg which is positive and statistically significant at the 10% level. Based on these placebo estimations, it is thus unlikely that our main finding of a negative and significant effect of industrial espionage on the productivity gap between West and East Germany is the result of probabilistic chance. To obtain a summary measure, we pool all available observations and estimate a regression on the full sample of countries, replacing the time- and sector-specific fixed effects in the individual country regressions with country/time- and country/sector-specific fixed effects. The resulting small and insignificant point estimate of -0.015 reported in column (2) suggests that there is indeed no relationship between East Germany's

[33] Reassuringly, however, the point estimates remain significant and actually become somewhat larger in magnitude if we exclude the arguably most sensitive sector to industrial espionage, *Office Appliances, Computers and Electronics*, from the sample.

[34] The correlation between the two instruments in our sample is 0.558, reflecting the fact that they capture different sources of variation in the inflow of information. Estimating the model using both instruments jointly yields an estimate of -0.124 (0.036), with a p-value for the overidentification test based on the Hansen J statistic of 0.860.

Table 5: Placebo Estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	GDR	All	AUS	AUT	BEL	DNK	ESP	FIN	FRA	GRC
Inflow/Y	-0.038**	-0.015	-0.026	0.010	0.096	-0.028	-0.021	0.020	-0.005	0.002
	(0.018)	(0.022)	(0.024)	(0.028)	(0.062)	(0.032)	(0.023)	(0.042)	(0.049)	(0.046)
Log Output/Worker Gap	-0.526***	-0.358***	-0.668***	-0.461***	-0.569***	-0.417**	-0.568***	-0.511***	-0.040	-0.314**
	(0.085)	(0.056)	(0.129)	(0.116)	(0.151)	(0.169)	(0.076)	(0.119)	(0.048)	(0.113)
R-squared	0.52	0.53	0.33	0.34	0.42	0.46	0.52	0.58	0.55	0.29
Observations	240	3945	225	225	225	225	225	225	225	225
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	IRL	ITA	JPN	KOR	LUX	NLD	PRT	SWE	UK	USA
Inflow/Y	0.116	0.021	-0.041	0.062	0.043*	-0.004	-0.042	-0.017	0.019	-0.059
	(0.092)	(0.038)	(0.061)	(0.058)	(0.022)	(0.021)	(0.030)	(0.030)	(0.020)	(0.075)
Log Output/Worker Gap	-0.044	-0.378***	-0.336***	-0.520***	-0.388	-0.737***	-0.435*	-0.449**	-0.261*	-0.560**
	(0.077)	(0.097)	(0.085)	(0.116)	(0.259)	(0.174)	(0.228)	(0.152)	(0.132)	(0.222)
R-squared	0.55	0.51	0.53	0.53	0.88	0.46	0.61	0.59	0.62	0.51
Observations	225	225	210	225	210	225	225	225	225	150

Note: 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 output per worker gap between West Germany and the country listed in the column heading over the period t to t+3. Data on output per worker for West Germany taken from the Heske data. Data on output per worker for all other countries taken from the EU KLEMS Growth and Productivity Accounts. Inflow/Y measured relative to East German sector-specific output as in Table 2. Column (1) reports results for the change in the log output per worker gap between West and East Germany along the lines of the right panel in Table 2. Column (2) reports the results from a pooled specification across all available countries in which we replace the time- and sector-specific fixed effects in the individual country regressions with country/time- and country/sector-specific fixed effects. Standard errors are clustered at the sectoral level, apart from column (2) where they are clustered at the country/sector level.

industrial espionage in the West and the relative productivity growth between West Germany and other uninvolved countries.

5.5 Quality of Information

In 1980, the Stasi started to systematically evaluate the quality of information received on a scale from one to five. In total, 40.1% of all pieces of information in our sample were qualitatively assessed in that way, with the vast majority receiving a value of three ("average value", 66.1%), a fair amount receiving a value of two ("valuable", 23.8%) and only a small fraction standing out with an assessment of one ("very valuable", 2.8%).[35]

Given the large volume of information received during the 1970s and 1980s, with more than 8,600 items per year on average, it is likely that relatively few pieces contained sufficiently novel and utilizable information to generate noticeable productivity gains in East Germany's economy. To allow for this type of heterogeneity, we estimate an extended specification in which we break down the overall measure of sector-specific espionage inflows into separate components according to the quality of the received information. Apart from the numerical quality assessments 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% of all pieces of information) or genuinely not quality-assessed (58.4%). Because of the frequency of missing quality informa-

[35] Since 1988, SIRA distinguishes between the date of arrival of a piece of information and the date of assessment of the quality of this information. Conditional on occurring at a later date, the quality assessment took place 124 days after arrival (10^{th} percentile 68 days, 90^{th} percentile 228 days). For consistency, throughout the analysis, we use the date of arrival as the relevant date based on which we assign a piece of information to a given year.

Table 6: Quality of Information

	Δ Log TFP Gap			Δ Log Output per Worker Gap		
	Main spec	Observed quality	Imputed quality	Main spec	Observed quality	Imputed quality
	(1)	(2)	(3)	(4)	(5)	(6)
Inflow/Y	-0.049***			-0.039**		
	(0.013)			(0.017)		
Quality - No Value		-2.258	-0.017		-1.156	0.100
		(1.670)	(0.241)		(1.895)	(0.198)
Quality - Low Value		0.009	-0.214***		-0.219	-0.259***
		(0.622)	(0.061)		(0.660)	(0.079)
Quality - Average Value		-0.039	-0.026		-0.030	-0.010
		(0.117)	(0.037)		(0.131)	(0.044)
Quality - Valuable		0.225	0.183		0.248	0.213
		(0.312)	(0.116)		(0.390)	(0.138)
Quality - Very Valuable		-1.538**	-1.661**		-1.603	-1.809**
		(0.701)	(0.633)		(0.975)	(0.619)
Quality - Missing		-0.067***	-0.049		-0.051*	-0.029
		(0.021)	(0.047)		(0.025)	(0.047)
Patents/Y Gap	-0.024	0.051	0.047	0.012	0.085	0.085
	(0.022)	(0.040)	(0.053)	(0.028)	(0.051)	(0.069)
Log TFP Gap	-0.589***	-0.586***	-0.609***			
	(0.097)	(0.098)	(0.085)			
Log Output/Worker Gap				-0.514***	-0.513***	-0.555***
				(0.100)	(0.104)	(0.097)
R-squared	0.55	0.56	0.56	0.51	0.52	0.54
Observations	240	240	240	240	240	240

Note: 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. Prior to the imputation procedure, 0.6% of the pieces of information in the sample were given a quality assessment of "No Value", 2.3% of "Low Value", 26.5% of "Average Value", 9.6% of "Valuable" and 1.1% of "Very Valuable", with the remaining 59.9% "Missing".

tion, 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 the expected quality of the informant generating the information. 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 first appeared in the SIRA database (compare the left panel of Figure A-2). 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, either through learning or through improved access to relevant material over time, for example as a result of career progression.[36] Figure A-8 in the appendix shows the distribution of quality assessments both before and after our imputation procedure, where we aggregate for better read-

[36] Interestingly, the estimated experience quality profile is almost flat so that the results based on these adjusted quality measures are very similar to those obtained by simply using the rounded average quality of the informant, calculated from all available assessments over the sample period.

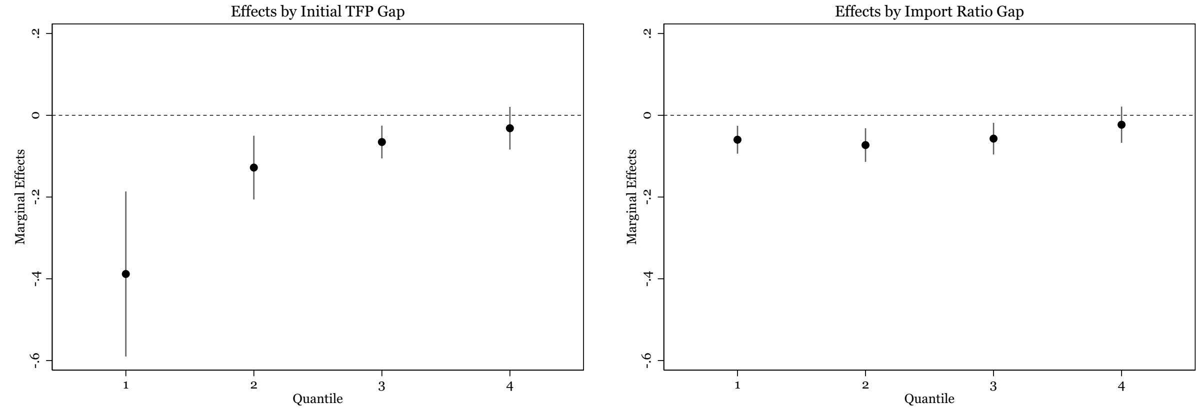
ability the quality values 1 and 2 into a "high" category, quality value 3 into a "medium" category, and quality values 4 and 5 into a "low" category. Overall, after the imputation, the coverage of quality information improves substantially, from 40.1% to 80.3%, distributed relatively evenly over the period considered.

Table 6 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 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 quality assessments. In spite of this lack of information, there is already some indication that the marginal effect of the highest quality information (-1.538 and -1.603) 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 high quality information, with point estimates of -1.661 for the log TFP gap and -1.809 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% 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.

5.6 Heterogeneity

In this section, we illustrate heterogeneous effects along two important dimensions, the initial TFP gap and the imports gap. By allowing the effects of industrial espionage to vary by the initial West-to-East log TFP gap, we relate our analysis to the literature that studies how R&D affects productivity growth depending on a country's distance to the technological frontier. Our starting point is the specification reported in column (6) of Table 3, in which we add the imports gap between West and East Germany as a potential additional driver of relative productivity growth to our main set of regressors. We then extend this specification by including interactions between the continuous variables (the information inflow, patents, and imports variables) and indicator variables for different quartiles in the initial log TFP gap, allowing the four dummy variables to substitute for the linear log TFP gap term. The left panel of Figure 6 depicts the results for the interaction effects with the inflow variable. While the estimate for the fourth quartile is statistically not significant with a point estimate of -0.032 (0.027), the estimates for the first, second and third quartiles are negative and statistically different from zero with point estimates of -0.388, -0.128 and -0.065, respectively. The four estimates are also statistically different from each other at conventional levels, indicating that industrial espionage was more effective in narrowing the productivity gap in industries where East Germany was technologically relatively close to West Germany. In these cases, East German researchers and engineers were presumably better able to

Figure 6: Heterogeneous Effects of Industrial Espionage



Note: The graphs plot the marginal effects from a specification in which the inflow of information variable is interacted with the quartiles of the initial log TFP gap (left panel) and the initial import intensity gap (right panel). Confidence intervals are constructed from standard errors clustered at the sectoral level.

implement the newly acquired technological knowledge from the West in their own production processes, suggesting that a sufficiently high absorptive capacity is a prerequisite for a successful exploitation of new espionage-based scientific-technical information. This result contrasts with existing findings of the returns to standard forms of R&D which suggest a larger return in industries further away from the frontier (Griffith et al., 2004).

As a second relevant dimension of heterogeneity, we examine the effect of industrial espionage along our measure of relative import barriers by interacting the inflow measure (as well as the patent gap and the initial log TFP gap) with different quartiles of the West-to-East import intensity gap (where we again substitute the linear import gap variable with the dummies for the different quartiles of the import gap). If industrial espionage serves as a form of technology transfer when regular channels such as trade are unavailable, one might expect larger-in-magnitude estimates in cases where, all else equal, the gap between West and East German import intensities is larger. The right panel of Figure 6 shows that there is no evidence for this hypothesis. The marginal effects across the four quartiles are similar in magnitude, with point estimates of -0.060 (0.015), -0.073 (0.017), -0.057 (0.021) and -0.023 (0.034), and statistically not 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 products 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 effects across sectors.

5.7 Additional Results

In this section, we show a number of additional results that shed further light on the link between industrial espionage and East German productivity growth. We start by allowing West and East German lagged TFP levels and patent intensities to appear separately in the regression, essentially relaxing the restrictions on the equality of some of the coefficients underlying equation (2). Comparing columns (1) and (2) of Table 7, this has qualitatively little bearing on our main parameter of interest, suggesting that the assumption of equal coefficients η_{it}^E and η_{it}^W, and θ_{it}^E and

Table 7: Additional Results

	Log TFP				Patenting	
	FRG/GDR		FRG	GDR	FRG	GDR
	(1)	(2)	(3)	(4)	(5)	(6)
Inflow/Y	-0.049***	-0.033***	-0.006	0.027**	-0.001	-0.115**
	(0.013)	(0.009)	(0.009)	(0.010)	(0.007)	(0.050)
Patents/Y Gap	-0.024					
	(0.022)					
Log TFP Gap	-0.589***					
	(0.097)					
GDR Patents/Y		-0.094	-0.036	0.058	0.033	0.105*
		(0.056)	(0.062)	(0.044)	(0.027)	(0.057)
FRG Patents/Y		-0.140**	-0.084	0.057	0.846***	-0.206***
		(0.063)	(0.073)	(0.077)	(0.036)	(0.070)
GDR Log TFP		0.593***	0.095	-0.498***	-0.074	0.008
		(0.098)	(0.098)	(0.089)	(0.046)	(0.143)
FRG Log TFP		-0.653***	-0.407***	0.246	0.056	0.085
		(0.101)	(0.136)	(0.153)	(0.062)	(0.220)
P-value WB	0.006	0.016	0.568	0.058	0.942	0.074
R-squared	0.55	0.56	0.67	0.46	0.99	0.97
Observations	240	240	240	240	240	240

Note: 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 (2), the change in log TFP between t and t+3 in West and East Germany, respectively, in columns (3) and (4), and the number of patent applications between t and t+3 per million euros of output in West and East Germany, respectively, in columns (5) and (6). Standard errors are clustered at the sectoral level. P-value WB denotes p-values, relating to the Inflow/Y estimate, from Cameron et al. (2008) clustered wild bootstraps using 1,000 replications.

θ^W_{it}, respectively, in equation (2) is rather innocuous.[37] Quantitatively, the higher flexibility of the specification in column (2) leads to an around 1/3 smaller estimated effect of the impact of industrial espionage on changes in the log TFP gap (from -0.049 to -0.033).

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 key finding has been that this reduction is driven by a growth-enhancing effect of industrial espionage on the East German economy. In columns (3) and (4) of Table 7, 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.[38] Indeed, our empirical results strongly support this intuition, by showing that the relationship between changes in the log TFP gap and East German industrial espionage

[37]Note that the sign of the coefficient on West German patent applications is the opposite of what one would expect if patent applications were a good proxy for productivity-enhancing R&D investments. However, as before, if one excludes the initial log TFP measures from the specification, the coefficients of West and East German patent intensities both have the expected sign, 0.051 (0.075) and -0.095 (0.111), respectively.

[38]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.

is almost exclusively driven by the latter's positive and significant effect on East German TFP growth (column (4)). The effect on West German TFP growth, in contrast, is close to zero and statistically not significant (column (3)).

In the last two columns of Table 7, we report results from a specification in which the dependent variable is the future patent intensity in West and East Germany. While industrial espionage has no effect on future patenting in West Germany (column (5)), it significantly reduces patenting in East Germany (column (6)), consistent with reports in Macrakis (2008) of industrial espionage essentially crowding out overt R&D in East Germany. In fact, internal estimates by the Stasi itself suggested that its industrial espionage had saved the East German economy about 75 million East German Mark in R&D expenditures (Macrakis, 2008).[39]

5.8 Counterfactual Simulations

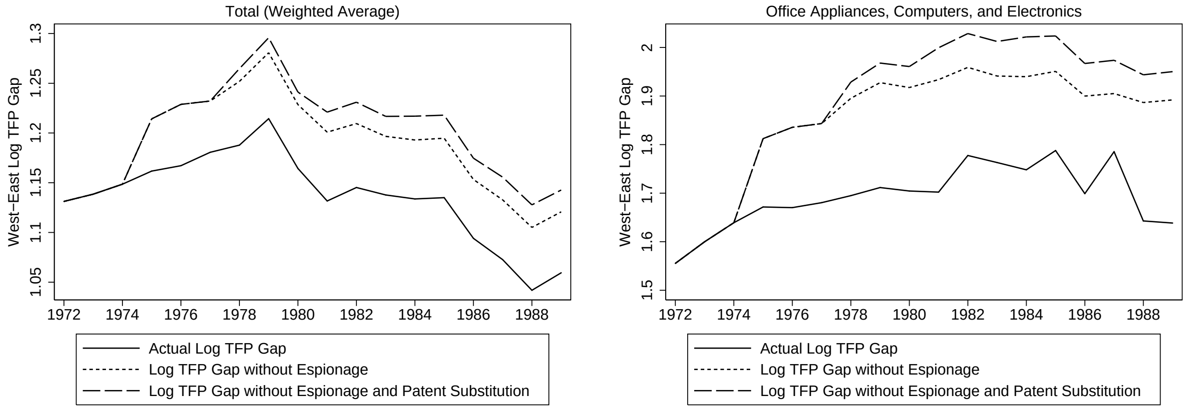
The empirical results from the previous section show that the Stasi's industrial espionage fostered East Germany's productivity growth while at the same time crowding out its overt R&D activities. Based on our estimates, we are able to simulate how TFP in East Germany would have evolved in the absence of industrial espionage. For this purpose, we set S_{jt}^{E}/Y_{jt}^{E} to zero for all industries and time periods and, starting with the first three-year period 1970-1972, forward-predict counterfactual productivity profiles for East Germany under two scenarios. In the first scenario, we assume that East Germany does not respond to the lack of knowledge transfer through industrial espionage by increasing its own patenting efforts, thus maintaining the actual patenting levels observed in the data. As suggested by our main findings, in the absence of industrial espionage, TFP growth in East Germany would be 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 -0.498 on the GDR Log TFP regressor in column (4) of Table 7). In the second scenario, we internalize the crowding out effect of industrial espionage on future patenting as suggested by the negative coefficient of -0.115 on the information inflow regressor in column (6) of Table 7. Without industrial espionage, East German patenting would thus increase which partly compensates the direct negative effect of industrial espionage on productivity growth (according to the positive coefficient of 0.058 on the GDR Patents/Y regressor in column (4) of Table 7). Finally, the increase in patenting would also have a secondary positive effect on TFP growth by fostering future patenting as suggested by the positive coefficient of 0.105 on the GDR Patents/Y regressor in column (6) of Table 7.[40]

The solid line in the left panel of Figure 7 displays the actual log TFP gap between West and East Germany between 1972 and 1989, which we construct as the difference in the employment-weighted average of the 16 sector-specific log TFP time series in both countries. The productivity gap initially increased from 1.13 log points (210%) in 1972 to 1.21 log points (235%) in 1979 before then decreasing to 1.06 log points (189%) in 1989. Allowing East Germany to react to the absence of industrial espionage by increasing its own patenting (scenario 2), the counterfactual productivity gap depicted by the short-dashed line reveals that the log TFP gap between West

[39] Note that East Germany may have been reluctant to patent innovations derived from its industrial espionage activities since that could jeopardize the position of their informants in the West.

[40] Even though the effect of changes in the level of East German TFP on future patenting is small with a coefficient of 0.008 (column (6), Table 7), we still use the new simulated TFP levels in our predictions of future patenting to be consistent with our approach in the TFP growth specification.

Figure 7: Counterfactual Simulations



Note: The graphs plot the counterfactual gap in log TFP between West and East Germany for all industry sectors (left panel) and for the *Office Appliances, Computers and Electronics* sector (right panel). To aggregate across all sectors, we take the employment-weighted average of each sector's actual and counterfactual log TFP time series. The counterfactual simulations are based on the empirical results reported in columns (4) and (6) of Table 7 for the full model without espionage and on column (4) only for the model without both espionage and patenting substitution.

and East Germany would have been about 0.061 log points (or 9.5%) bigger at the end of the time period (207%). Assuming that East Germany's patenting does not respond to the absence of industrial espionage (scenario 1) would lead to a further widening of the log TFP gap by another 0.022 log points on average.[41] Overall, industrial espionage thus played a noticeable but, given the size of the actual gap, quantitatively modest role in bringing East Germany's productivity closer to its West German counterpart.

The right panel of Figure 7 shows the corresponding actual and counterfactual log TFP gaps for the *Office Appliances, Computers and Electronics* sector, by far the sector most targeted by East Germany's industrial espionage (see Figure 2). Contrary to the overall development, the actual log TFP gap between West and East Germany in this sector widened over time, from 1.56 log points (376%) in 1972 to 1.64 log points (416%) in 1989. In the absence of industrial espionage, this divergence would have been significantly more pronounced, reaching 1.89 log points (562%) with full patent substitution and 1.95 log points (603%) without any East German patent response in 1989. Evidently, in this fast-changing sector, while not sufficient to reduce the technological gap with West Germany, industrial espionage at least helped East Germany to avoid falling significantly further behind. Figure A-9 in the appendix shows the corresponding figures 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, especially due to the lack of reliable information on the cost side, we can use existing estimates to get a rough idea about this important question. As it happens, the Stasi itself produced annual estimates of the economic benefits 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 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

[41] Note that due to the 3-year intervals employed in our main specification and the lag structure between dependent and independent variables, the first time period in which actual and counterfactual TFP in East Germany can diverge is 1975, and the first time period in which the predicted increase in patenting can generate an additional effect is 1978.

the 1980s (Vogel, 2008). Our own results point to even larger benefits of around 4.6 billion euros, which translate into around 7.3 billion Deutsche Mark in 1988.[42] 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 (Deutscher Bundestag, 1998). While these figures should be viewed with caution, taken together they suggest a very high return on the investment in industrial espionage.

6 Concluding Remarks

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, combined with comprehensive industry-level data, provide a unique opportunity for studying this question. Our estimates 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.

In addition to this main result, our finding of a crowding out of standard forms of R&D suggests that the Western trade embargoes on the East, coupled with an abundance of intelligence sources in strategically important locations, lowered the cost of industrial espionage relative to R&D in East Germany. Under its communist regime, where investments in espionage likely exhibited economies of scale, this may have helped East Germany to catch up with its capitalist neighbors. However, these investments presumably lost much of their value after German unification in 1990, at which point Western firms had decades of experience in conducting productive R&D while Eastern firms lost their primary sources of technological know-how. Whether the East German economy's dependence on industrial espionage bore some responsibility for its poor post-unification performance is an interesting question for future research.

Arguably, few contemporary intelligence agencies have been able to make industrial espionage as effective a tool as the Stasi did during the Cold War. While, since then, the relative benefits of industrial espionage may have declined due to more integrated international markets and easier access to new ideas through legitimate channels, its 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[43], making the topic as relevant today as it was at the height of the Cold War.

Due to the particular institutional setting that prevailed in East Germany during the period analyzed, there are a few issues that could limit the external validity of our findings. These include the discrepancy between East Germany's planned economy and today's market-based economies,

[42] The figure of 4.6 billion euros is constructed based on the results from scenario 2 of our counterfactual simulations by dividing the total gross value added across the 16 industry sectors in East Germany in 1988 (measured in 1995 million euros) by 1.065 (the ratio of actual to counterfactual East German TFP) and subtracting the resulting counterfactual gross value added (70,146 million euros) from the actual total gross value added (74,706 million euros). The conversion into current Deutsche Mark in 1988 is based on the exchange rate between Deutsche Mark and the euro (1.95583:1) and changes in the consumer price index in Germany between 1988 and 1995. Note that in 1988, the inofficial exchange rate between East German Mark and Deutsche Mark was around 4.4:1 (Thieme, 1998).

[43] See, for example, ONCIX, 2011, "Foreign Spies Stealing U.S. Economic Secrets in Cyberspace: Report to Congress on Foreign Economic Collection and Industrial Espionage, 2009–2011", p. i, or BKA, 2014, "Wirtschaftsspionage und Konkurrenzausspähung – eine Analyse des aktuellen Forschungsstandes", p. 5.

the extensive trade embargoes against the entire communist bloc at the time which severely limited standard forms of technology transfer, and the fundamental shift in the technology of spying in recent decades away from human intelligence towards IT-based methods of information acquisition.[44] However, the processes through which newly acquired information is translated into productivity growth today are unlikely to differ much from the processes in place in East Germany at the time of the Cold War, especially in countries characterized by strong centralized governments such as China and Russia. Moreover, even today countries such as Iran and North Korea continue to face restrictions on technology transfers through economic sanctions, making industrial espionage a particularly attractive method of knowledge acquisition. While the success with which East Germany penetrated West German commercial and scientific institutions may have been unique, the main insights from studying this particular episode in the long history of industrial espionage are thus relevant for modern times as well.

[44] The role of human informants, however, remains an important one even today. For example, recent survey data from a representative sample of almost 7,000 German companies show that 33% of affected companies believe the perpetrator(s) of the information theft to be among their own employees (Corporate Trust, 2014).

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Appendix Tables

Table A-1: Keyword Allocation

				Sector																	
Rank	Original Keyword	English Translation	Freq.	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	Other Sector	Unclassified
1.	Objekt	Object	19,786																		✓
2.	Militaertechnik	Military Technology	12,471																	✓	
3.	Elektronik	Electronics	11,807													✓					
4.	Elektrotechnik	Electrical Engineering	11,307													✓					
5.	S	-	10,968																		✓
6.	Austausch_Ausgeschlossen	Exchange Precluded	10,419																		✓
7.	Mikroelektronik	Microelectronics	9,666													✓					
8.	Software	Software	9,645													✓					
9.	Rechentechnik	Computer Science	9,046													✓					
10.	Nachrichtentechnik	Communications Engineering	7,868					✓								✓					
11.	Chemie	Chemistry	7,519								✓										
12.	R	-	5,734																		✓
13.	Anwendung	Application	5,331																		✓
14.	NA	-	5,312																		✓
15.	Hardware	Hardware	4,326													✓					
16.	Technologie	Technology	3,734																		✓
17.	MT	-	3,582																		✓
18.	EDV	Electronic Data Processing	3,416													✓					
19.	Kleinrechner	Microcomputer	3,343													✓					
20.	Programm	Program	3,335													✓					
21.	Beschreibung	Description	3,166																		✓
22.	Umweltschutz	Environment Protection	3,085																		✓
23.	Datentechnik	Data Processing Technology	3,060													✓					
24.	Muster	Pattern	3,034		✓				✓							✓					
25.	EDVA	Electronic Data Processing Facility	3,018													✓					
26.	Metallurgie	Metallurgy	2,992											✓							
27.	Optik	Optics	2,922													✓					
28.	Personalcomputer	Personal Computer	2,722													✓					
29.	IBM	IBM	2,635													✓					
30.	Kernkraftwerk	Nuclear Power Plant	2,584																✓		
⋮	⋮	⋮	⋮																		
1991.	Schwermetall	Heavy Metal	57											✓							
1992.	Schwingquarz	Oscillating Crystal	57													✓					
1993.	Soman	Soman	57								✓									✓	
1994.	Temperaturverteilung	Temperature Distribution	57																✓		
1995.	Turbinenschaufel	Turbine Blade	57												✓						
1996.	Umkehrosmose	Reverse Osmosis	57	✓															✓	✓	
1997.	Verformung	Deformation	57																		✓
1998.	Verkehr	Traffic	57																	✓	
1999.	Waermedaemmung	Heat Insulation	57																	✓	
2000.	Wolfram	Wolfram	57								✓										

Note: This tables shows the 2,000 most common keywords in TDB11 and their sectoral allocation. List of sectors: 1. Food and Tobacco, 2. Textiles and Clothing, 3. Leather Products, 4. Woodworking, 5. Paper, Printing, and Publishing, 6. Furniture, Jewelry, and Music Instruments, 7. Coking and Petroleum, 8. Chemicals, 9. Rubber and Plastics, 10. Glass, Ceramics, and other non-Metalic Minerals, 11. Metalworking, 12. Machine Building, 13. Office Appliances, Computers, and Electronics, 14. Automobiles, 15. Mining, 16. Utilities–Energy and Water Supply.

Table A-2: Top 20 Informants, 1968 - 1989

Registration	Code Name	Pieces of Information	Reliability	First Active Year	Last Active Year
(1)	(2)	(3)	(4)	(5)	(6)
XV/6603/80	FROEBEL	5,344	A	1982	1989
XV/2768/76	SEEMANN	4,902	A	1970	1988
XV/1967/64	KOREN	4,257	A	1973	1987
XV/78/71	ZENTRUM	3,373	A	1969	1989
XV/436/70	IRMGARD KRUEGER	3,288	A	1970	1989
	DR. GROSZ	2,630	A	1969	1974
XV/1754/68	RING	2,485	A	1968	1978
XV/2550/74	HERZOG	2,239	A	1974	1989
XV/2234/74	JUERGEN	1,631	A	1969	1987
XV/2110/67	OPTIK	1,472	A	1969	1989
XV/4070/70	LORENZ	1,374	B	1971	1979
XV/3074/78	SCHNEIDER	1,347	B	1969	1989
XV/6412/82	PICHLER	1,157	A	1982	1989
XV/238/68	RITTER	1,123	B	1969	1986
XV/47/68	ERICH	1,068	A	1971	1988
XV/450/86	ZELTER	1,065	B	1984	1989
XV/3/75	HARTMANN	1,043	A	1969	1981
XV/2001/73	JACK	944	A	1973	1987
XIV/14/69	ALFRED	890	A	1970	1989
XV/1508/75	WEBER	867	A	1969	1980

Note: Reliability is measured by the mode of the recorded assessments. An “A” denotes “reliable” (*zuverlässig*), a “B” denotes “trustworthy” (*vertrauenswürdig*), a “C” denotes “not checked” (*nicht überprüft*), a “D” denotes “questionable” (*fragwürdig*), and an “E” denotes “double agent” (*Doppelagent*). Only values A, B and C appear in the data.
*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A-3: Summary Statistics - by Sector

	West Germany		East Germany		Difference	
	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
Food and Tobacco						
Inflow/Y			0.180	(0.020)		
Δ Log TFP	0.036	(0.052)	0.020	(0.054)	0.016	(0.084)
Δ Log Output per Worker	0.052	(0.050)	0.044	(0.043)	0.008	(0.074)
Patents/Y	0.078	(0.013)	0.016	(0.009)	0.063	(0.021)
Log TFP	1.992	(0.085)	1.922	(0.028)	0.070	(0.079)
Log Output per Worker	3.428	(0.106)	2.966	(0.051)	0.463	(0.062)
Imports/Y	1.448	(0.158)	0.147	(0.017)	1.301	(0.147)
Textiles and Clothing						
Inflow/Y			1.359	(0.306)		
Δ Log TFP	0.064	(0.033)	0.094	(0.059)	-0.030	(0.060)
Δ Log Output per Worker	0.090	(0.034)	0.153	(0.057)	-0.063	(0.065)
Patents/Y	0.399	(0.046)	0.169	(0.060)	0.230	(0.098)
Log TFP	1.807	(0.097)	-0.066	(0.140)	1.873	(0.053)
Log Output per Worker	3.099	(0.136)	0.849	(0.221)	2.250	(0.091)
Imports/Y	3.904	(0.864)	1.225	(0.315)	2.678	(0.908)
Leather Products						
Inflow/Y			2.000	(0.184)		
Δ Log TFP	0.022	(0.025)	-0.026	(0.086)	0.048	(0.089)
Δ Log Output per Worker	0.053	(0.038)	0.032	(0.059)	0.021	(0.059)
Patents/Y	0.207	(0.041)	0.232	(0.116)	-0.025	(0.082)
Log TFP	1.923	(0.030)	0.508	(0.092)	1.416	(0.115)
Log Output per Worker	3.123	(0.073)	1.298	(0.048)	1.825	(0.058)
Imports/Y	2.138	(0.600)	0.324	(0.139)	1.814	(0.497)
Woodworking						
Inflow/Y			2.213	(0.416)		
Δ Log TFP	-0.009	(0.045)	0.060	(0.061)	-0.069	(0.049)
Δ Log Output per Worker	0.004	(0.043)	0.104	(0.093)	-0.100	(0.082)
Patents/Y	0.153	(0.031)	0.065	(0.076)	0.087	(0.058)
Log TFP	2.189	(0.038)	0.429	(0.083)	1.760	(0.104)
Log Output per Worker	3.523	(0.029)	1.343	(0.158)	2.181	(0.157)
Imports/Y	1.167	(0.262)	0.272	(0.113)	0.896	(0.283)
Paper, Printing, and Publishing						
Inflow/Y			0.810	(0.144)		
Δ Log TFP	0.010	(0.043)	0.047	(0.025)	-0.037	(0.046)
Δ Log Output per Worker	0.043	(0.047)	0.092	(0.024)	-0.049	(0.050)
Patents/Y	0.286	(0.034)	0.024	(0.013)	0.262	(0.044)
Log TFP	2.318	(0.030)	2.003	(0.064)	0.316	(0.048)
Log Output per Worker	3.672	(0.077)	3.056	(0.125)	0.616	(0.055)
Imports/Y	0.764	(0.129)	0.122	(0.046)	0.643	(0.125)

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Table A-3 – continued from previous page

	West Germany		East Germany		Difference	
	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
Furniture, Jewelry, and Music Instruments						
Inflow/Y			2.936	(0.525)		
Δ Log TFP	-0.010	(0.052)	0.062	(0.068)	-0.072	(0.094)
Δ Log Output per Worker	0.009	(0.044)	0.106	(0.061)	-0.097	(0.077)
Patents/Y	0.153	(0.014)	0.265	(0.165)	-0.112	(0.159)
Log TFP	2.412	(0.044)	0.471	(0.112)	1.941	(0.147)
Log Output per Worker	3.720	(0.030)	1.452	(0.167)	2.268	(0.170)
Imports/Y	0.932	(0.278)	0.068	(0.015)	0.864	(0.288)
Coking and Petroleum						
Inflow/Y			0.230	(0.037)		
Δ Log TFP	0.018	(0.145)	0.109	(0.058)	-0.091	(0.141)
Δ Log Output per Worker	0.055	(0.188)	0.144	(0.059)	-0.090	(0.170)
Patents/Y	0.246	(0.041)	0.039	(0.008)	0.207	(0.045)
Log TFP	2.831	(0.099)	2.932	(0.174)	-0.102	(0.133)
Log Output per Worker	4.775	(0.156)	4.592	(0.227)	0.182	(0.152)
Imports/Y	18.242	(6.799)	0.045	(0.019)	18.197	(6.801)
Chemicals						
Inflow/Y			2.205	(0.538)		
Δ Log TFP	0.082	(0.081)	0.088	(0.031)	-0.006	(0.089)
Δ Log Output per Worker	0.100	(0.086)	0.128	(0.034)	-0.028	(0.086)
Patents/Y	1.034	(0.248)	0.926	(0.205)	0.108	(0.428)
Log TFP	2.117	(0.147)	1.013	(0.132)	1.104	(0.050)
Log Output per Worker	3.663	(0.175)	2.473	(0.192)	1.189	(0.051)
Imports/Y	2.202	(0.328)	0.594	(0.152)	1.608	(0.249)
Rubber and Plastics						
Inflow/Y			2.969	(0.977)		
Δ Log TFP	0.044	(0.054)	-0.002	(0.064)	0.047	(0.066)
Δ Log Output per Worker	0.061	(0.051)	0.058	(0.057)	0.003	(0.063)
Patents/Y	0.353	(0.125)	0.226	(0.083)	0.127	(0.172)
Log TFP	2.249	(0.082)	0.903	(0.051)	1.346	(0.100)
Log Output per Worker	3.576	(0.107)	2.093	(0.087)	1.483	(0.046)
Imports/Y	0.504	(0.097)	0.115	(0.030)	0.389	(0.089)
Glass, Ceramics, and other Non-Metallic Minerals						
Inflow/Y			0.833	(0.215)		
Δ Log TFP	0.038	(0.057)	0.041	(0.119)	-0.003	(0.112)
Δ Log Output per Worker	0.072	(0.052)	0.077	(0.126)	-0.005	(0.113)
Patents/Y	0.282	(0.038)	0.123	(0.059)	0.159	(0.088)
Log TFP	2.217	(0.060)	1.096	(0.087)	1.121	(0.084)
Log Output per Worker	3.670	(0.110)	2.373	(0.123)	1.297	(0.084)
Imports/Y	0.647	(0.110)	0.055	(0.016)	0.592	(0.097)

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Table A-3 – continued from previous page

	West Germany		East Germany		Difference	
	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
Metalworking						
Inflow/Y			1.174	(0.318)		
Δ Log TFP	0.037	(0.050)	0.034	(0.057)	0.003	(0.081)
Δ Log Output per Worker	0.050	(0.052)	0.087	(0.054)	-0.037	(0.084)
Patents/Y	0.416	(0.032)	0.236	(0.083)	0.180	(0.112)
Log TFP	2.099	(0.061)	0.315	(0.053)	1.784	(0.058)
Log Output per Worker	3.522	(0.083)	1.623	(0.141)	1.899	(0.088)
Imports/Y	1.478	(0.192)	0.816	(0.149)	0.662	(0.146)
Machine Building						
Inflow/Y			0.498	(0.144)		
Δ Log TFP	0.014	(0.051)	0.057	(0.041)	-0.043	(0.070)
Δ Log Output per Worker	0.036	(0.053)	0.094	(0.052)	-0.058	(0.082)
Patents/Y	0.584	(0.063)	0.472	(0.086)	0.113	(0.139)
Log TFP	2.481	(0.040)	1.520	(0.074)	0.961	(0.053)
Log Output per Worker	3.735	(0.072)	2.577	(0.120)	1.158	(0.060)
Imports/Y	0.811	(0.160)	0.219	(0.023)	0.592	(0.146)
Office Appliances, Computers, and Electronics						
Inflow/Y			5.339	(0.611)		
Δ Log TFP	0.073	(0.032)	0.055	(0.056)	0.018	(0.065)
Δ Log Output per Worker	0.113	(0.043)	0.110	(0.061)	0.003	(0.081)
Patents/Y	1.453	(0.309)	1.684	(0.272)	-0.231	(0.530)
Log TFP	2.157	(0.124)	0.463	(0.072)	1.694	(0.063)
Log Output per Worker	3.438	(0.191)	1.466	(0.146)	1.972	(0.057)
Imports/Y	1.000	(0.175)	0.214	(0.072)	0.786	(0.153)
Motor Vehicles						
Inflow/Y			1.208	(0.383)		
Δ Log TFP	0.017	(0.055)	0.047	(0.053)	-0.031	(0.080)
Δ Log Output per Worker	0.047	(0.054)	0.108	(0.053)	-0.061	(0.086)
Patents/Y	0.396	(0.060)	0.408	(0.090)	-0.012	(0.120)
Log TFP	2.404	(0.051)	0.990	(0.066)	1.414	(0.047)
Log Output per Worker	3.819	(0.094)	2.041	(0.149)	1.778	(0.069)
Imports/Y	1.147	(0.216)	0.355	(0.046)	0.792	(0.231)
Mining						
Inflow/Y			0.177	(0.052)		
Δ Log TFP	-0.051	(0.060)	0.009	(0.055)	-0.060	(0.090)
Δ Log Output per Worker	-0.028	(0.060)	0.043	(0.049)	-0.071	(0.087)
Patents/Y	0.146	(0.035)	0.080	(0.024)	0.066	(0.032)
Log TFP	2.061	(0.073)	1.845	(0.049)	0.217	(0.116)
Log Output per Worker	3.704	(0.048)	3.374	(0.093)	0.330	(0.132)
Imports/Y	1.188	(0.277)	0.041	(0.018)	1.147	(0.266)

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Table A-3 – continued from previous page

	West Germany		East Germany		Difference	
	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
Utilities - Energy and Water Supply						
Inflow/Y			0.260	(0.061)		
Δ Log TFP	0.020	(0.113)	0.035	(0.068)	-0.014	(0.150)
Δ Log Output per Worker	0.045	(0.113)	0.066	(0.067)	-0.021	(0.149)
Patents/Y	0.083	(0.015)	0.042	(0.012)	0.041	(0.026)
Log TFP	2.367	(0.062)	2.757	(0.082)	-0.390	(0.119)
Log Output per Worker	4.393	(0.069)	4.587	(0.125)	-0.194	(0.128)
Imports/Y	0.083	(0.011)	0.000	(0.000)	0.083	(0.011)

Note: Summary statistics computed for 3-year overlapping observations for the period 1970 to 1989. 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 is 15 for each industry.

Table A-4: Industrial Espionage and Productivity - Non-overlapping Observations

	Log TFP			Log Output per Worker		
	Baseline spec	Patents gap	Lagged gap	Baseline spec	Patents gap	Lagged gap
	(1)	(2)	(3)	(4)	(5)	(6)
Inflow/Y	-0.034	-0.046*	-0.049**	-0.026	-0.041*	-0.042*
	(0.021)	(0.022)	(0.018)	(0.020)	(0.022)	(0.022)
Patents/Y Gap		0.105***	0.006		0.137***	0.045
		(0.030)	(0.033)		(0.032)	(0.042)
Log TFP Gap			-0.569***			
			(0.135)			
Log Output/Worker Gap						-0.478***
						(0.139)
P-value WB	0.060	0.058	0.016	0.134	0.104	0.156
R-squared	0.34	0.39	0.59	0.32	0.40	0.54
Observations	80	80	80	80	80	80

Note: Sample based on 3-year intervals and non-overlapping observations for the years 1973, 1976, 1979, 1982, and 1985. 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. P-value WB denotes p-values, relating to the Inflow/Y estimate, from Cameron et al. (2008) clustered wild bootstraps using 1,000 replications.

Table A-5: Robustness - Log TFP

	Main spec	Weighted by output	No weights	No IT	Sector trends	Trade gap	Flexible capital shares	Keyword weighted	Machine learning
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1-Year Intervals									
Inflow/Y	-0.031***	-0.050**	-0.028**	-0.021	-0.032***	-0.029***	-0.030***	-0.052***	-0.050***
	(0.010)	(0.019)	(0.013)	(0.020)	(0.009)	(0.009)	(0.010)	(0.008)	(0.008)
Patents/Y Gap	-0.070	-0.082	-0.032	0.049	-0.065	-0.068	-0.060	-0.070	-0.068
	(0.046)	(0.069)	(0.045)	(0.118)	(0.089)	(0.044)	(0.049)	(0.044)	(0.044)
Log TFP Gap	-0.261***	-0.289***	-0.211***	-0.249***	-0.548***	-0.262***	-0.242***	-0.264***	-0.265***
	(0.040)	(0.054)	(0.042)	(0.038)	(0.095)	(0.042)	(0.043)	(0.040)	(0.040)
Imports/Y Gap						-0.007			
						(0.008)			
P-value WB	0.290	0.114	0.164	0.256	0.294	0.318	0.308	0.094	0.188
R-squared	0.25	0.31	0.21	0.24	0.35	0.25	0.24	0.25	0.26
Observations	304	304	304	285	304	298	304	304	304
3-Year Intervals									
Inflow/Y	-0.049***	-0.076**	-0.047***	-0.043**	-0.043***	-0.047***	-0.044***	-0.086***	-0.046**
	(0.013)	(0.032)	(0.014)	(0.017)	(0.012)	(0.013)	(0.013)	(0.024)	(0.018)
Patents/Y Gap	-0.024	-0.022	0.002	0.022	0.013	-0.019	-0.020	-0.017	-0.023
	(0.022)	(0.044)	(0.032)	(0.045)	(0.076)	(0.023)	(0.025)	(0.020)	(0.017)
Log TFP Gap	-0.589***	-0.783***	-0.565***	-0.595***	-1.201***	-0.592***	-0.574***	-0.606***	-0.602***
	(0.097)	(0.172)	(0.091)	(0.095)	(0.095)	(0.102)	(0.107)	(0.087)	(0.087)
Imports/Y Gap						-0.001			
						(0.003)			
P-value WB	0.010	0.044	0.044	0.060	0.008	0.014	0.012	0.003	0.044
R-squared	0.55	0.58	0.54	0.54	0.70	0.55	0.54	0.55	0.53
Observations	240	240	240	225	240	234	240	240	240
5-Year Intervals									
Inflow/Y	-0.031	-0.062*	-0.029**	-0.005	-0.015	-0.029	-0.027	-0.079**	-0.044*
	(0.022)	(0.034)	(0.013)	(0.022)	(0.027)	(0.022)	(0.023)	(0.030)	(0.024)
Patents/Y Gap	-0.003	0.018	-0.006	-0.043	0.069	-0.003	0.001	0.012	0.010
	(0.027)	(0.041)	(0.025)	(0.041)	(0.131)	(0.028)	(0.029)	(0.021)	(0.038)
Log TFP Gap	-0.832***	-1.089***	-0.838***	-0.852***	-1.296***	-0.783***	-0.800***	-0.847***	-0.836***
	(0.113)	(0.253)	(0.115)	(0.113)	(0.264)	(0.079)	(0.121)	(0.112)	(0.111)
Imports/Y Gap						-0.000			
						(0.003)			
P-value WB	0.204	0.174	0.162	0.818	0.708	0.254	0.282	0.008	0.062
R-squared	0.70	0.69	0.73	0.70	0.73	0.70	0.70	0.71	0.70
Observations	176	176	176	165	176	170	176	176	176

Note: Sample based on 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 (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 $t+x$, where $x \in \{1, 3, 5\}$. Column (1) restates our main results corresponding to 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 construct our TFP measures using sector-specific capital shares. In column (8), we weight each piece of information according to the number of categorized keywords assigned to each sector. In column (9), we use machine learning methods to assign pieces of information to industry sectors. Standard errors clustered at the sectoral level in parentheses. P-value WB denotes p-values, relating to the Inflow/Y estimate, from Cameron et al. (2008) clustered wild bootstraps using 1,000 replications.

Table A-6: Robustness - Log Output per Worker

	Main spec	Weighted by output	No weights	No IT	Sector trends	Trade gap	Keyword weighted	Machine learning
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-Year Intervals								
Inflow/Y	-0.031**	-0.046**	-0.024*	-0.013	-0.045***	-0.030**	-0.058***	-0.055***
	(0.012)	(0.019)	(0.013)	(0.015)	(0.009)	(0.012)	(0.009)	(0.008)
Patents/Y Gap	-0.035	-0.058	0.004	0.116	-0.047	-0.031	-0.036	-0.035
	(0.058)	(0.083)	(0.060)	(0.144)	(0.093)	(0.056)	(0.056)	(0.057)
Log Output/Worker Gap	-0.227***	-0.297***	-0.209***	-0.229***	-0.524***	-0.224***	-0.231***	-0.234***
	(0.043)	(0.065)	(0.054)	(0.041)	(0.096)	(0.042)	(0.042)	(0.043)
Imports/Y Gap						-0.005		
						(0.009)		
P-value WB	0.538	0.282	0.298	0.336	0.038	0.564	0.222	0.242
R-squared	0.24	0.32	0.20	0.23	0.34	0.24	0.25	0.26
Observations	304	304	304	285	304	298	304	304
3-Year Intervals								
Inflow/Y	-0.039**	-0.070*	-0.036**	-0.025	-0.049***	-0.037**	-0.073**	-0.044*
	(0.017)	(0.035)	(0.015)	(0.022)	(0.012)	(0.017)	(0.026)	(0.022)
Patents/Y Gap	0.012	0.024	0.031	0.053	0.080	0.017	0.017	0.013
	(0.028)	(0.050)	(0.035)	(0.062)	(0.075)	(0.029)	(0.026)	(0.025)
Log Output/Worker Gap	-0.514***	-0.730***	-0.539***	-0.548***	-1.200***	-0.525***	-0.535***	-0.538***
	(0.100)	(0.181)	(0.100)	(0.109)	(0.107)	(0.099)	(0.096)	(0.098)
Imports/Y Gap						-0.004		
						(0.003)		
P-value WB	0.116	0.098	0.114	0.288	0.002	0.142	0.006	0.186
R-squared	0.51	0.53	0.48	0.48	0.71	0.52	0.51	0.51
Observations	240	240	240	225	240	234	240	240
5-Year Intervals								
Inflow/Y	-0.018	-0.045	-0.010	0.016	-0.005	-0.016	-0.066*	-0.040
	(0.025)	(0.039)	(0.016)	(0.025)	(0.026)	(0.024)	(0.032)	(0.027)
Patents/Y Gap	0.029	0.052	0.013	-0.026	0.153	0.029	0.048	0.049
	(0.038)	(0.057)	(0.037)	(0.051)	(0.129)	(0.039)	(0.030)	(0.045)
Log Output/Worker Gap	-0.779***	-1.085***	-0.848***	-0.834***	-1.361***	-0.728***	-0.798***	-0.797***
	(0.136)	(0.246)	(0.142)	(0.144)	(0.249)	(0.110)	(0.138)	(0.139)
Imports/Y Gap						-0.000		
						(0.002)		
P-value WB	0.574	0.364	0.584	0.568	0.924	0.636	0.110	0.106
R-squared	0.69	0.68	0.69	0.68	0.75	0.69	0.70	0.70
Observations	176	176	176	165	176	170	176	176

Note: Sample based on 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 (apart from columns (2) and (3)). The dependent variable is the change in the log output per worker gap between West and East Germany over the period t to $t + x$, where $x \in \{1, 3, 5\}$. Column (1) restates our main results corresponding to column (6) 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. P-value WB denotes p-values, relating to the Inflow/Y estimate, from Cameron et al. (2008) clustered wild bootstraps using 1,000 replications.

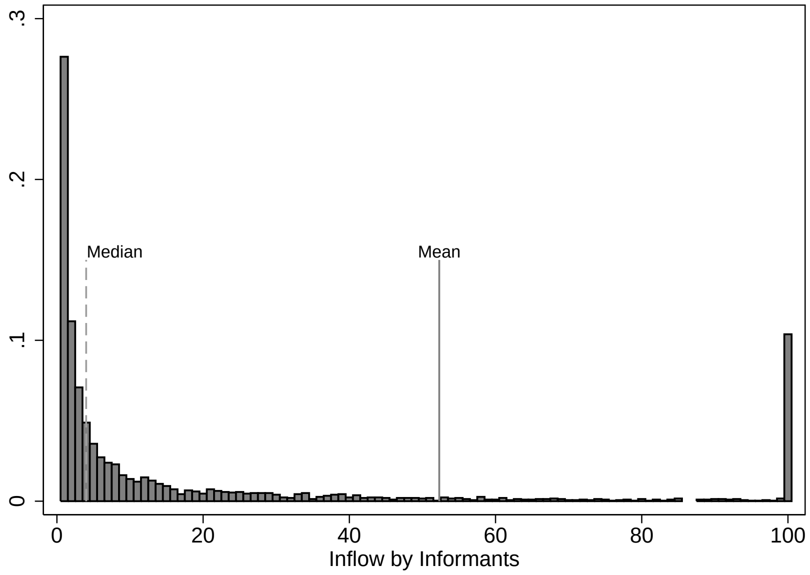
Table A-7: Robustness - Capital Shares and Depreciation Rates

	$\alpha = 0.20$			$\alpha = 0.33$		
	$\delta = 0.02$	$\delta = 0.06$	$\delta = 0.10$	$\delta = 0.02$	$\delta = 0.06$	$\delta = 0.10$
	(1)	(2)	(3)	(4)	(5)	(6)
Inflow/Y	-0.042***	-0.045***	-0.046***	-0.044***	-0.049***	-0.052***
	(0.014)	(0.014)	(0.015)	(0.013)	(0.013)	(0.013)
Patents/Y Gap	-0.007	-0.011	-0.015	-0.019	-0.024	-0.030
	(0.025)	(0.025)	(0.025)	(0.024)	(0.022)	(0.022)
Log TFP Gap	-0.546***	-0.564***	-0.579***	-0.567***	-0.589***	-0.607***
	(0.101)	(0.101)	(0.100)	(0.101)	(0.097)	(0.093)
P-value WB	0.036	0.024	0.024	0.016	0.006	0.008
R-squared	0.52	0.53	0.54	0.53	0.55	0.57
Observations	240	240	240	240	240	240
	$\alpha = 0.40$			α flexible		
	$\delta = 0.02$	$\delta = 0.06$	$\delta = 0.10$	$\delta = 0.02$	$\delta = 0.06$	$\delta = 0.10$
	(1)	(2)	(3)	(4)	(5)	(6)
Inflow/Y	-0.046***	-0.051***	-0.054***	-0.041***	-0.044***	-0.046***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.014)
Patents/Y Gap	-0.026	-0.030	-0.036*	-0.013	-0.020	-0.027
	(0.023)	(0.021)	(0.020)	(0.025)	(0.025)	(0.026)
Log TFP Gap	-0.578***	-0.599***	-0.616***	-0.543***	-0.574***	-0.605***
	(0.101)	(0.094)	(0.087)	(0.103)	(0.107)	(0.112)
P-value WB	0.008	0.002	0.002	0.022	0.018	0.016
R-squared	0.53	0.56	0.58	0.52	0.54	0.55
Observations	240	240	240	240	240	240

Note: 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. TFP measures constructed using the perpetual inventory method, assuming the capital shares (α) and depreciation rates (δ) reported in the column headings. In the bottom right panel, the capital shares are allowed to vary across sectors and are constructed as the average sector-specific capital shares over the period 1970 to 1989 reported in the EU KLEMS Growth and Productivity Accounts. Standard errors are clustered at the sectoral level. P-value WB denotes p-values, relating to the Inflow/Y estimate, from Cameron et al. (2008) clustered wild bootstraps using 1,000 replications.

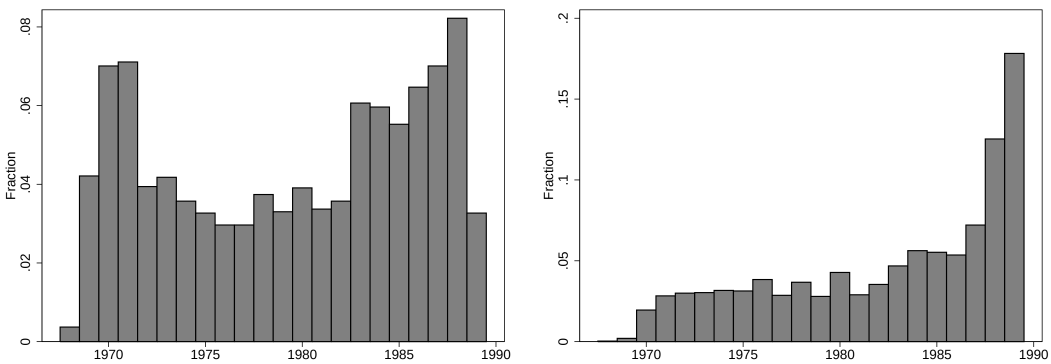
Figures

Figure A-1: Inflow Distribution Across Informants



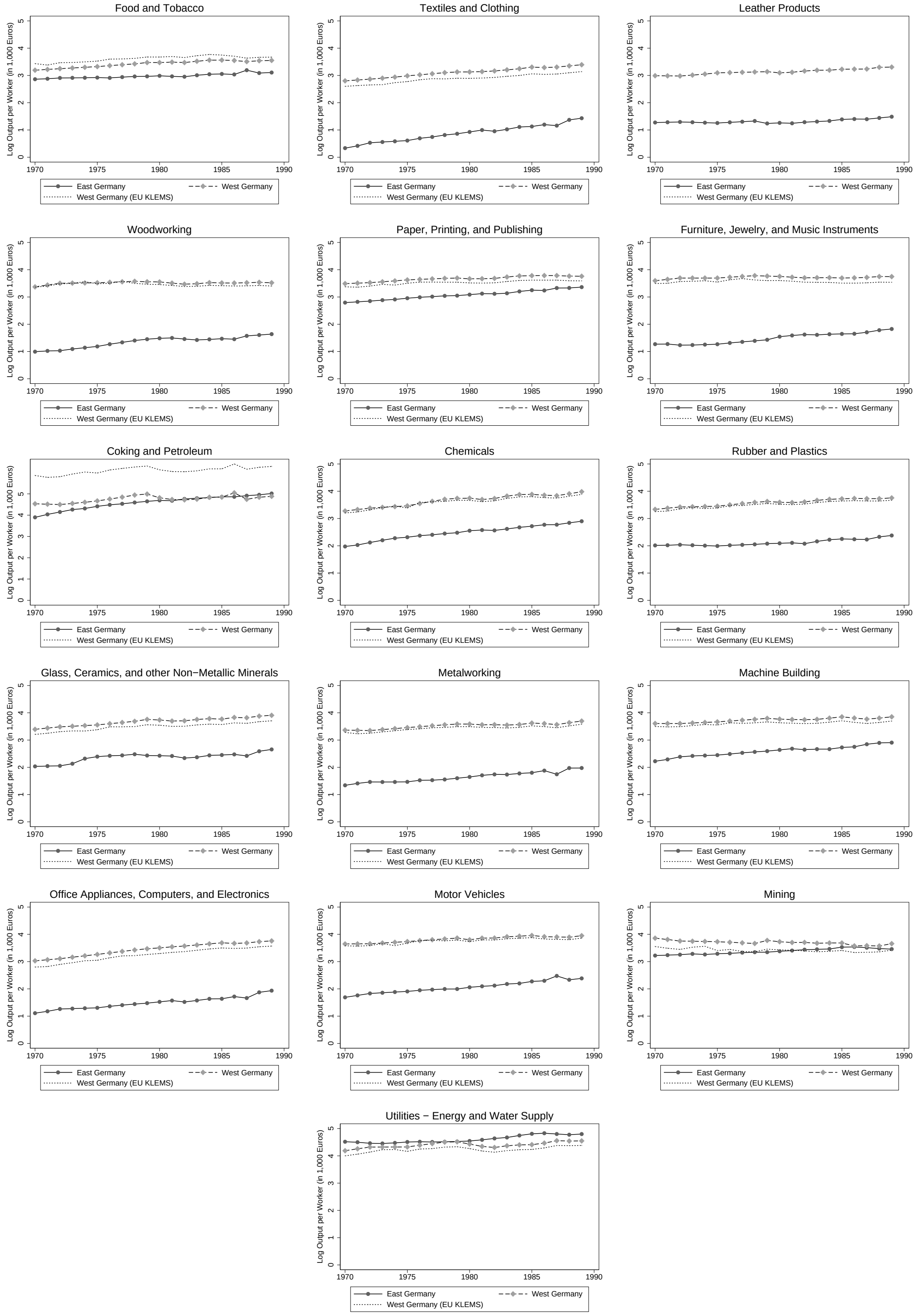
Note: The figure shows the distribution of the total number of pieces of information received from individual informants. Observations are censored at a value of 100 for better readability.

Figure A-2: First and Last Active Year



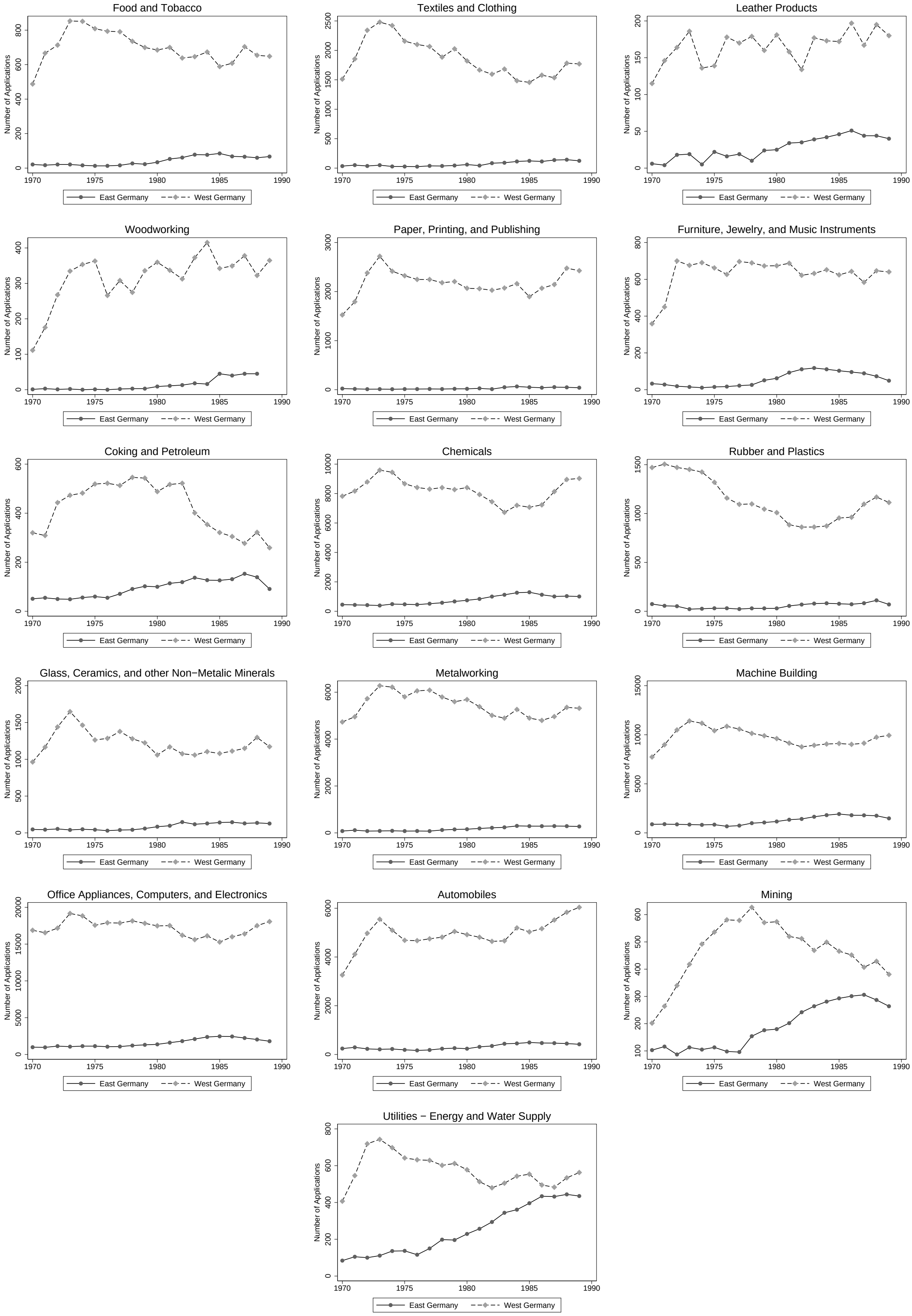
Note: The figure shows the distributions of the first (left panel) and last year (right panel) in which individual informants are observed in the data.

FIGURE A-3: LOG OUTPUT PER WORKER BY SECTOR



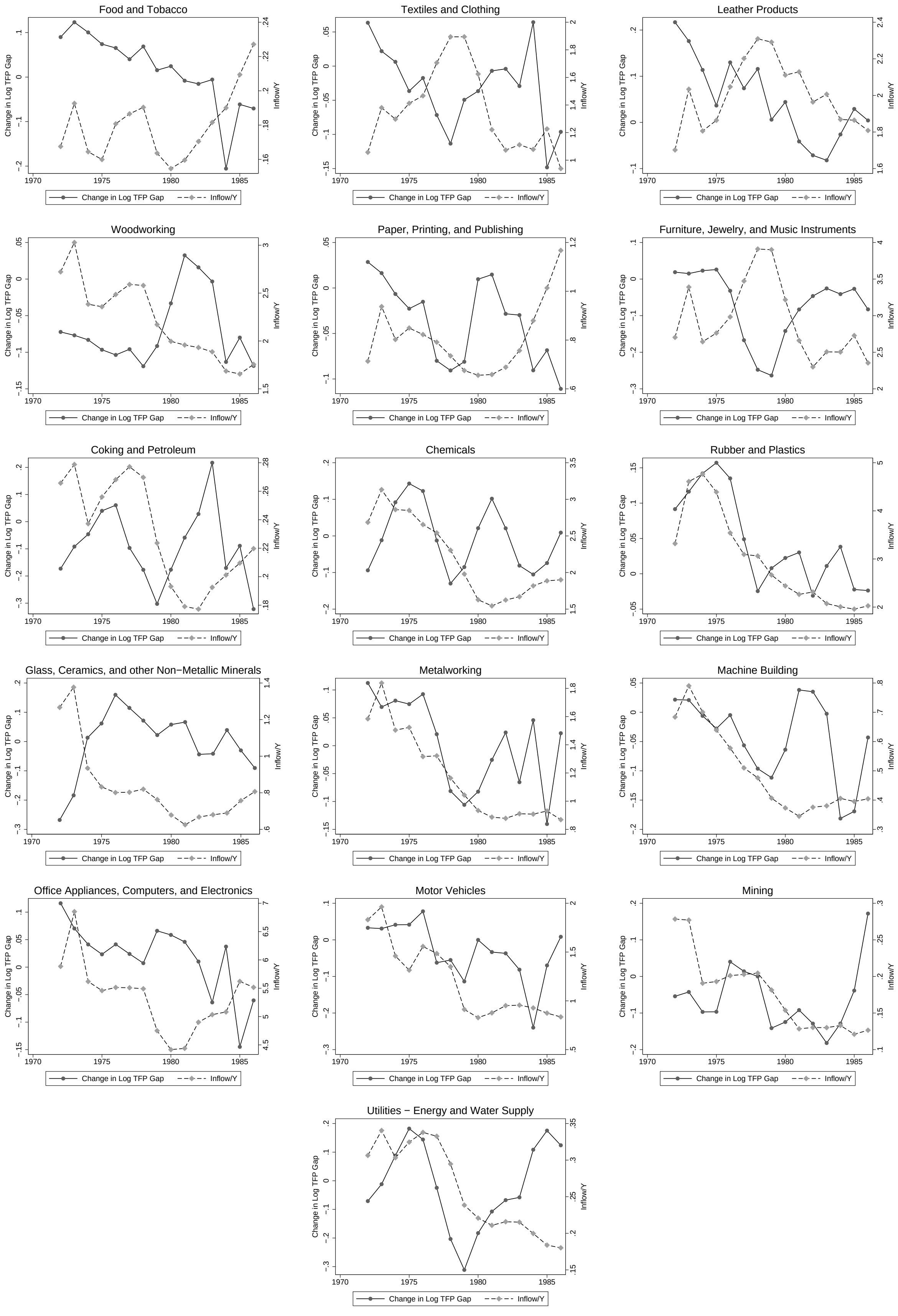
Note: The individual panels depict the log of gross value added per worker by sector for West and East Germany over the period 1970 to 1989.

Figure A-4: Patent Applications by Sector



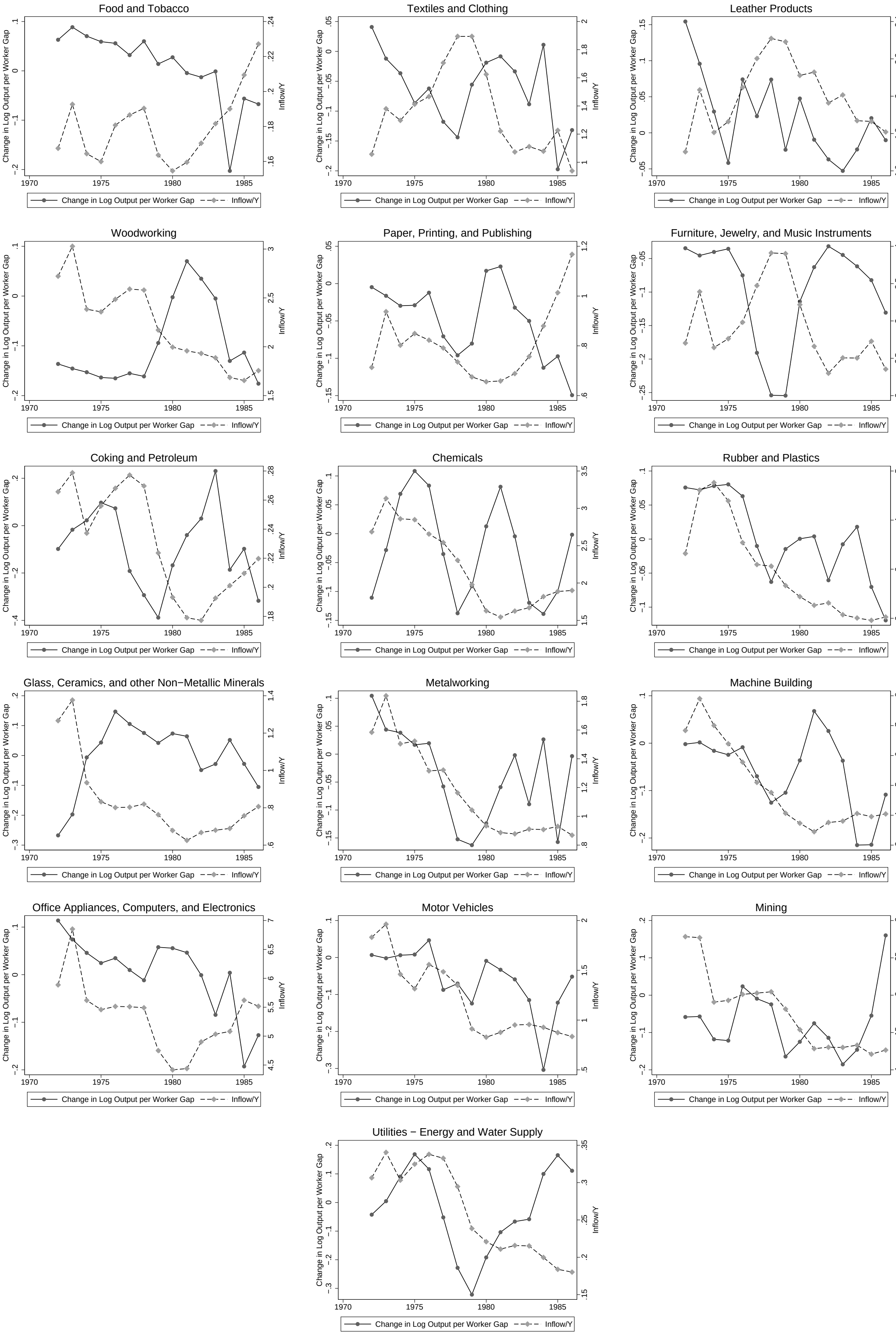
Note: The individual panels depict the number of patent applications in West and East Germany for the corresponding sectors over the period 1970 to 1989.

Figure A-5: Change in Log TFP Gap and Information Inflow



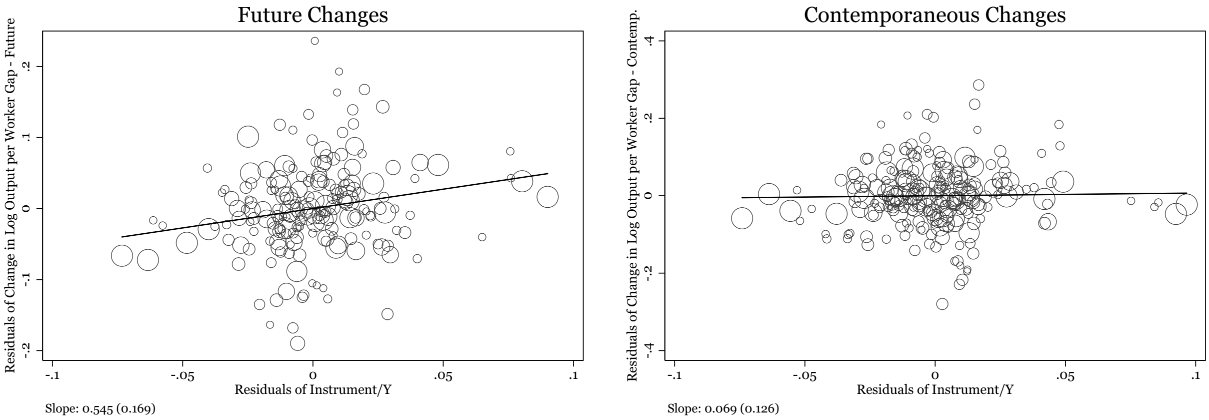
Note: The individual panels depict for each sector the change in the log TFP gap between West and East Germany between t and t+3 and the accumulated inflow of information scaled by output between t-3 and t.

Figure A-6: Change in Log Output per Worker Gap and Information Inflow



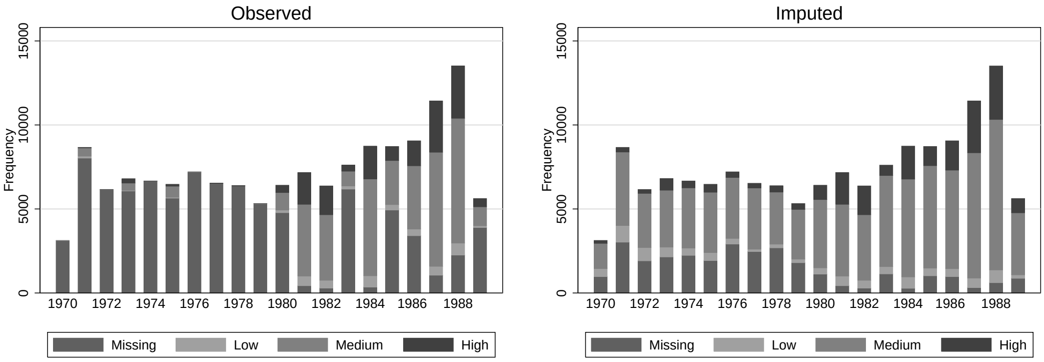
Note: The individual panels depict for each sector the change in the log output per worker gap between West and East Germany between t and t+3 and the accumulated inflow of information scaled by output between t-3 and t.

Figure A-7: Exits of Informants and Changes in the Log Output per Worker Gap



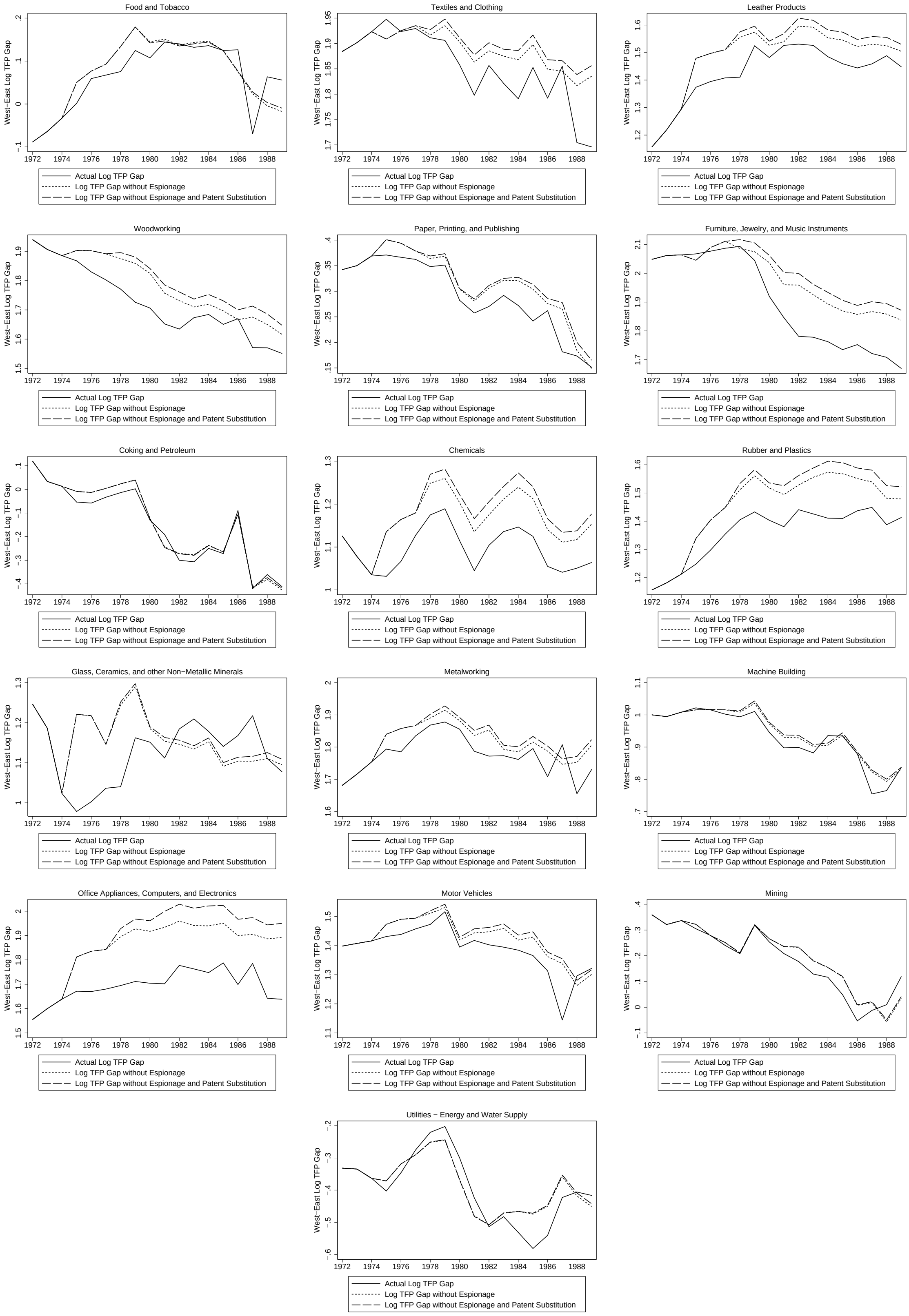
Note: The figure plots residualized changes in the log output per worker gap between West and East Germany against residualized exits of highly prolific informants scaled by output. Exits are measured between the end of period t-6 and t-3. Changes in the log output per worker gap are measured between the end of period t and t+3 in the left panel and the end of t-6 and t-3 in the right panel. 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.

Figure A-8: Distribution of Quality Assessments



Note: The figure shows the distribution of quality assessments by year, both as observed in the data (left panel) and after imputing missing observations using the experienced-adjusted expected quality assessments of the informant generating the information (right panel). "Low" comprises assessments of 4 and 5, "Medium" assessments of 3, and "High" comprises assessments of 1 and 2.

Figure A-9: Counterfactual Simulations by Sector



Note: The individual panels depict the counterfactual gap in log TFP between West and East Germany in the corresponding sectors. The counterfactual simulations are based on the empirical results reported in columns (4) and (6) of Table 7 for the full model without espionage and the results in column (4) only for the model without espionage and patenting substitution, holding patenting constant.