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Working Paper in Economics

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July 2025

No. 438

ISSN: 1439-2305

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Trade and Soft Power:
Evidence from the China Shock in Africa

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Abstract

Global powers increasingly use trade as a tool of geopolitical influence. But can trade also foster soft power? We provide novel evidence on this relationship by combining geo-referenced survey data from 22 African countries sourced from the Gallup World Poll with Chinese import data. Exploiting plausibly exogenous variation in manufacturing imports induced by the "China shock," we find that trade does not affect African citizens' attitudes towards China in the aggregate. However, the China shock is associated with higher perceived incomes and contributes to more favorable views of China in African countries with low technological intensity. Most notably, among citizens in democratic regimes, increased trade exposure is associated with more favorable perceptions of China, suggesting that political context mediates the effectiveness of trade-based soft power.

Acknowledgments: We thank Lukas Wellner for his thoughtful comments and discussion. Moreover, we thank Andreas Fuchs for his input and Atanas Spasov for diligent proofreading. We gratefully acknowledge funding support from the Leibniz Association grant K316/2020.

Keywords: Trade, soft power, China-Africa, China shock, Gallup World Poll

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1 Introduction

In recent decades, Africa has become a focus of geopolitical competition for economic powers such as China, the European Union (EU) and the United States (US). The EU remained Africa's largest trading partner in the colonial and postcolonial periods, as well as in the 21st century. However, trade with China expanded massively, particularly following its accession to the World Trade Organization (WTO) in 2001. While the EU's share of total imports to Sub-Saharan Africa declined from 35.7 percent in 2000 to 24.1 percent in 2020, China's share increased more than fivefold over the same period – from just 3.6 percent to 20 percent (World Bank, 2025).[1] China's export surge has elicited critical responses across the globe. While several recent papers document how exposure to Chinese trade fosters protectionist and even authoritarian attitudes (Ballard-Rosa et al., 2021; Feigenbaum and Hall, 2015; Colantone and Stanig, 2018a,b), public perceptions of China appear largely unaffected and remain particularly favorable in many African countries.[2] In this respect, China's rapid rise in trade is not merely economic—it is deeply strategic. Policies such as the "going-out" strategy, the Forum on China–Africa Cooperation (FOCAC), and the Belt and Road Initiative (BRI) reflect a deliberate effort by Beijing to expand its footprint and influence across the African continent. In this light, trade flows are not just commercial transactions, but also a channel through which global powers compete for long-term alignment. Eventually, countries may not only export goods, but also soft power to win foreign "hearts and minds" (Eichenauer et al., 2021). In this paper, we ask whether China's exports to Africa affect public opinion towards China. Public opinion is a commonly used proxy for soft power (e.g., Nye, 2004; Goldsmith and Horiuchi, 2012; Wellner et al., 2025; Rose, 2016).

China's emergence as the world's leading exporting nation, along with its adverse impact on manufacturing employment and secondary economic outcomes is relatively well studied (Autor et al., 2013; Edwards and Jenkins, 2015; Acemoglu et al., 2016; Malgouyres, 2017; Colantone and Stanig, 2018a; Darko et al., 2021; Dippel et al., 2022; Nedoncelle and Wolfersberger, 2023; Ngoma, 2023), but there is only sparse and country-level evidence on the effects of Chinese trade on public opinion (Eichenauer et al., 2021). Until now, academics studying China's soft power in Africa have primarily examined the role of Beijing's development finance (Jones, 2018; Blair et al., 2022; Wellner et al., 2025) or, when focused on trade, have lacked causal identification (Kleinberg and Fordham, 2010; Hanusch, 2012). We thus enhance the existing literature by

[1] See also Appendix Figure 4.

[2] For instance, a recent article by the China Global South Project titles "China Tops Favorability Rankings in Africa, Outpacing U.S. and EU [...]."

providing causal micro-evidence on how import competition from China affected its soft power in the African context.

The theoretical relationship between import competition and soft power mediated by an individual's economic situation within a given country remains ambiguous ex-ante. Chinese imports can affect labor market outcomes through two principal channels: the competition channel and the input channel. Through the competition channel, domestic producers face intensified competition from imports of Chinese goods. This may lead to a reduction in either manufacturing employment, wages, or both, if domestic firms lose market share (Autor et al., 2013; Acemoglu et al., 2016). The input channel operates differently: it can enhance manufacturing employment and increase wages by providing domestic firms with access to higher-quality and more affordable intermediate goods, thereby lowering production costs and boosting productivity. However, the overall impact of these opposing forces may differ substantially in African economies compared to in advanced countries with more developed manufacturing sectors (Ngoma, 2023). In this context, the "premature deindustrialization" argument advanced by Rodrik (2016) is particularly relevant. It suggests that, due to the adverse effects of trade liberalization on the manufacturing sector and value-added activities, Africa may fail to reach the levels of industrialization experienced by earlier industrializing countries. This would hamper the chances of income convergence, global value chain integration, and thus challenge the traditional path of economic development. Whether individuals perceive and attribute consequences to Chinese import competition and whether their attitudes are shaped positively or negatively, remains an empirical question (Kleinberg and Fordham, 2010; Eichenauer et al., 2021).

Against this background, we provide causal micro-level evidence on how African individuals adjust their perceptions of China in response to the China shock. Thereby, we contribute to the existing literature by applying the China shock framework to a novel outcome of interest – soft power. Our cross-country setting in Africa offers a comprehensive assessment with an identification strategy that enables the estimation of causal effects.

Specifically, this paper examines whether manufacturing imports from China affect African citizens' attitudes toward China. We derive a region-specific measure of import exposure to China – the so-called China shock – inspired by the well-known approach by Autor et al. (2013), originally applied in industrialized country settings. We leverage information on imports from countries external to Africa to build a credible instrumental variable, which we then link to survey data from more than 140,000 individuals collected by the Gallup World Poll (GWP) over the period 2008-2020 (Gallup, 2020). This approach allows us to causally assess the impact of trade on China's soft power.

On average, we find no evidence that imports from China affect the level of approval of the Chinese government. We run multiple robustness checks, which alter our instrument, outcome variable or consider different timing, but find no consistent evidence for an average soft power effect. However, our heterogeneity analysis reveals that China seems to be effective in increasing African citizens' perceived income and cultivating soft power among African citizens living in countries with low technology intensity. Moreover, we observe some positive associations in countries with a history of democracy and in those that were recently visited by the Chinese leader.

The remainder of this paper is structured as follows: Section 2 outlines theoretical and empirical considerations of soft power and its link to trade shocks. Section 3 presents the data in detail and the empirical strategy to estimate the effects of import competition on soft power. Section 4 discusses the corresponding results, the underlying mechanisms, and their robustness. Section 5 concludes.

2 Trade and Soft Power

Soft power refers to a country's capacity to shape the preferences and behavior of others through appeal and attraction rather than coercion (Nye, 2004, p. x). Nye (2004) distinguishes three pillars of soft power: culture, political values, and foreign policies. Culture represents the appeal of a nation's ideological and cultural identity, often conveyed through non-state actors and civil society. Political values refer to the principles upheld domestically. Foreign policy involves the ways a nation conducts itself in international affairs, including international institutions, law, cooperation, and trade.

Like other major powers, China is actively pursuing soft power. Since joining the WTO in 2001, it has become the world's largest exporter and the primary trade partner for most countries, including many across Africa. Soft power is a central pillar of this global endeavor, featuring prominently in official discourse and policy priorities (China Daily, 2007; The Economist, 2017). In 2014, President Xi Jinping explicitly framed the BRI — the world's largest aid, trade, and infrastructure program — as a vehicle to "increase China's soft power, give a good Chinese narrative, and better communicate China's message to the world" (People's Daily, 2014). Since taking office, Xi has repeatedly emphasized soft power in key speeches, reflecting its strategic importance in advancing China's global influence and reshaping public perceptions around the globe.

Soft power matters, also because it is an important first-order aim for many second-order strategic goals. Soft power can influence foreign public opinion in ways that gather support, from diplomatic goals to military cooperation (Goldsmith and Horiuchi, 2012). Higher levels of affinity between populations can increase trade flows and yield economic benefits (Guiso et al., 2009; Rose, 2016, 2019). Soft power therefore represents an important and consequential policy tool, in particular for economic powers, such as China.

Trade can affect soft power in several ways. First, trade might shape public perceptions based on the economic effects of its economic impact (Kleinberg and Fordham, 2010). Free trade stimulates competition, and this increases pressure on domestic producers. Chinese import competition, for instance, leads to significant job losses, wage declines, and reduced labor force participation in the US, in particular in regions more exposed to the China shock (Autor et al., 2013; Acemoglu et al., 2016). This effect is particularly pronounced among low-skilled workers; as domestic firms lose market share, their sales and revenues decline, and some businesses are forced to exit the market, resulting in further job losses and sectoral downturns (Giovannetti and Sanfilippo, 2009; Ngoma, 2023).

The economic effects can also yield political consequences. In line with the Stolper-Samuelson theorem, trade liberalization can create substantial discontent with globalization, in particular among the disadvantaged (Mayda and Rodrik, 2005; Milner, 2018). Import competition affects domestic political attitudes, diminishes support for democratic institutions, and gives rise to protectionist trade policy preferences (Milner, 2018). As far as individuals associate the deteriorating economic conditions with the rise of a single trading partner, this can reflect on popular attitudes towards that country and foster the support of protectionist and populist policies. Autor et al. (2020) show that this has been a driving factor in the political polarization of US politics in the past decade, and similar effects have been documented across Europe (Colantone and Stanig, 2018a; Ballard-Rosa et al., 2021; Milner, 2021; Steiner and Harms, 2021; Dippel et al., 2022).

Yet, free trade might also have a positive economic impact. As countries specialize, goods become more affordable and accessible (Hanusch, 2012). This can spur innovation, as imports encourage domestic firms to improve efficiency and adopt new technologies leading to productivity gains and higher-skilled employment (Chen et al., 2009; Bloom et al., 2016; Darko et al., 2021; Ngoma, 2023). This might enhance employment and wage prospects and even foster value-chain upgrading in downstream sectors. Any such economic improvements are likely to be positively perceived and thereby promoting relations with the trading partner among the public.

Trade can also affect soft power through goodwill and cultural channels. The first relates to the material dimension of trade, where the presence and perceived quality of foreign goods and technologies shape public attitudes toward the trading partner. When imports are viewed as affordable, reliable, or beneficial to local economic development——such as through the availability of consumer goods or productivity—enhancing industrial inputs—this can enhance the exporting country's image. Second, trade might increase exposure to foreign cultures, which can reduce prejudice and foster more positive intergroup attitudes (Allport, 1954; Mansfield and Mutz, 2009; Fetzer and Schwarz, 2021). High levels of bilateral trade can help disseminate information, facilitate interpersonal and institutional exchange and cultural practices. These interactions can humanize the trading partner, promote familiarity, and improve bilateral perceptions (Pettigrew, 1998; Disdier and Mayer, 2007). This exchange can occur through both exposure to foreign goods and through exposure to foreign labor, which plays an important role in Sino-African trade relations in general, and Chinese infrastructure development in Africa in particular (Mohan, 2013; Cervellati et al., 2022).

Whether or not trade affects soft power in Africa is likely to depend on the impact of the China shock on individual livelihoods, for as long as such a change is also reflected upon the trade partner China. If the import competition channel dominates, increased trade exposure is likely to reduce Chinese soft power in Africa. While such an effect is well documented among high-income countries, less is known about the consequences in low- and middle-income countries. Poorer regions of the world, in particular countries in Africa, often lag a strong manufacturing sector, and might therefore be less exposed to import competition from China (Ngoma, 2023). Indeed, Rodrik (2016) argues that trade liberalization prevented the formation of a solid manufacturing base in many developing countries challenging the traditional path of economic development.

On the African continent, therefore, the other channels might be more relevant. Access to relatively lower-cost, higher-quality, or previously unavailable foreign goods might stimulate innovation and productivity, potentially boosting employment and wages. These input-driven gains are especially relevant in African contexts, where firms often face constraints in sourcing quality inputs. If such benefits are realized and recognized by local populations, Chinese import competition could foster more favorable views of China (Hanusch, 2012; Darko et al., 2021; Ngoma, 2023). If price and input factors dominate, higher trade exposure could lead to soft power gains.

Hanusch (2012) confirms results from previous polls that Chinese presence in Africa is in general well perceived, using individual-level data from the fourth round of the Afrobarometer survey in 2008. However, the support declines in response to negative perceptions of Chinese imports and, relative to attitudes toward the US, concerns about democracy. By contrast, perceptions of China's role in poverty alleviation significantly boost support. Similarly, but on a wider sample consisting of 47 countries around the world, including several African countries, Kleinberg and Fordham (2010) show that higher levels of imports from China are associated with negative public perceptions of China. However, among low-income countries, there is no such relation. The authors argue that while consumers may benefit from greater variety or lower prices, some workers may face job losses due to foreign competition, explaining such mixed evidence. Moving beyond correlations, Eichenauer et al. (2021) employ repeated cross-sectional survey data and an instrumental variables strategy to assess the impact of Chinese trade, aid, and investment on public perceptions of China in Latin America. They find no significant average effect of trade on public opinion. However, and similar to the reported effects across high-income countries, their results suggest that economic engagement may contribute to increased polarization in attitudes toward China.

This paper is the first to plausibly identify the soft power effects of Chinese trade in Africa. We employ individual-level survey data from the Gallup World Poll spanning 22 African countries over a time period from 2008 to 2020. Using this large, cross sectional survey data for more than 130,000 individuals, we deploy an instrumental variable (IV) approach that exploits exogenous variation from China's ascent as major trade partner—the China shock. This allows us to causally identify the effects of trade on soft power. Using the rich, individual-level data also allows us to advance the existing literature in disentangling different channels in the relation between trade and soft power. We do so using the empirical methodology outlined in the following section.

3 Empirical Strategy

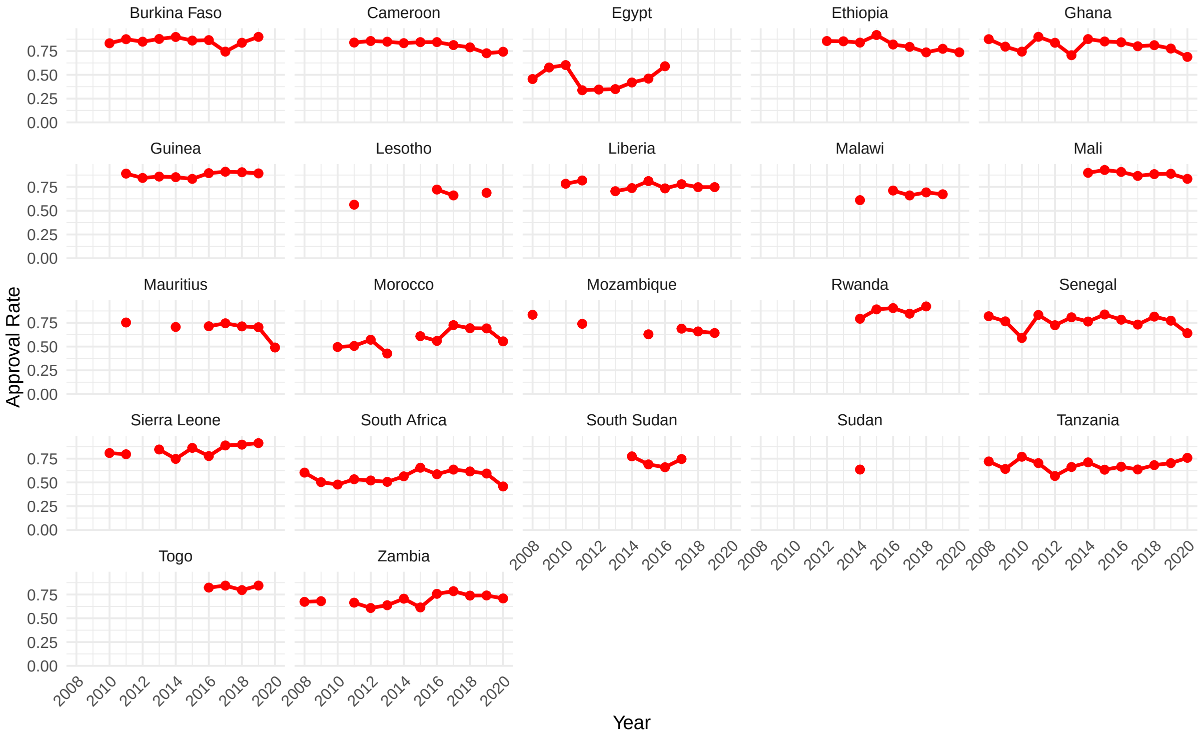
We estimate the effects of trade of soft power in African countries using individual level data from the GWP (Gallup, 2020). Specifically, we use the question "Do you approve or disapprove of the job performance of the leadership of China?".[3] The question constitutes a common measure of soft power used in both qualitative and quantitative analysis (The Economist, 2019; Wellner et al., 2025). The variable is also positively correlated with a more direct (yet significantly less frequently sampled) variable of the Gallup, which asks more directly about the opinion of China (Wellner et al., 2025), as well as other measures of soft power from Pew Research Center's Global Attitudes and Trends (Goldsmith et al., 2021).[4] The GWP gathers repeated cross-sectional public opinion data worldwide, representative at the national level of residents aged 15 and above. Typically, each country wave consists of 1,000 participants including a

[3] We drop the answers "Don't know" and "Refused," totaling 2,508 observations. Figure 3 provides an overview of the distribution of the sample across years and countries.

[4] For an in-depth exploration of the measurement challenges associated with (Chinese) soft power, particularly with opinion polls, please consult Blanchard and Lu (2012) and Ohnesorge (2020, pp. 181-184).

regional identifier, which allows mapping the respondent-level data to ADM1 regions.[5] Figure 1 shows that the coverage of the outcome variable varies across African countries and time.

Figure 1: Average support for China by country over time (2008-2020)



Notes: The red line illustrates the average share of GWP respondents approving of China's leadership by country over the 2008-2020 period.

We then use these individual perceptions of China as outcome variable in the following regression framework:

$$Approval\ of\ China_{jcrt} = \beta_0 + \beta_1 Imports_{crt} + \sigma X_{jt} + \theta_{ct} + \mu_r + \epsilon_{jcr} \quad (1)$$

where the $Approval\ of\ China_{jcrt}$ is a binary variable that takes the value of one if individual j in region r of country c in year t approves of China, and zero otherwise. $Imports$ measures Chinese imports in current US dollar (USD) using data from the World Integrated Trade Solutions (WITS) database (World Bank, 2022).[6]

X_{jt} represents a set of individual level control variables, including the respondent's age,

[5]The GWP includes variables named REGION_xxx that indicate the sub-national region an individual lives in. We use these variables to perform a string match to region names from the ADM1 shapefiles (Hijmans et al., 2018). In instances where GWP regions could not be matched with ADM1 regions, it resulted from the GWP utilizing a geo reference situated between the unit of ADM1 regions and the country level (the case for 11 Moroccan regions) or due to unmatchable names (as with two regions in Lesotho). In total, we mapped 603 African ADM1 regions from the GWP.

[6]We downloaded the data at HS 2-digit level according to the Harmonized System (HS) 1988/92. HS 2-digit product codes spanning from 28 to 99 are classified as manufacturing products.

age square, gender, education, and whether or not the respondent lives in an urban area.[7] θ_{ct} denotes country-year fixed effects, which control for confounding factors at the national level that change over time, such as national economic conditions and policies, including trade agreements or national events and shocks that affect all regions of the country equally. The country-year fixed effects cover for instance the 2008 Beijing Olympics, which may have boosted both African-Chinese trade and soft power across the world. μ_r denote region fixed effects, which control for any time-invariant characteristics of provinces, such as geography (e.g., distance to the capital city and the sea), as well as structural differences across regions (e.g.,urbanization or infrastructure level). ϵ_{jcr} is the error term. We cluster standard errors by region, accounting for any within-region correlation of the error terms.[8]

The OLS regression described exploits variation in exposure to Chinese imports over time within provinces, netting out all shocks that are common across regions in the same country and year through the inclusion of country-year fixed effects. This design absorbs national-level trends—such as shifts in foreign policy, macroeconomic fluctuations, or media narratives—as well as time-invariant characteristics of provinces, such as historical trade ties or long-standing political preferences. Yet, despite this relatively strict level of fixed effects, any time-varying factors that are specific to a region remain as a potential source of endogeneity.

One of these endogeneity concerns is omitted variable bias. Economic dynamics at the province level—such as changes in industrial composition, labor market disruptions, or shifts in political climate—could simultaneously influence both the extent of Chinese import penetration and public attitudes toward China. For instance, a decline in local manufacturing employment may be both a consequence of rising import competition and a trigger for growing dissatisfaction with foreign economic partners. As Autor et al. (2013) emphasize, import shocks are not randomly distributed but are shaped by structural features that may also correlate with unobserved determinants of soft power.

Another potential threat to identification is reverse causality. Trade flows may not be exogenous to public opinion: countries or regions where China enjoys a more favorable image might receive preferential trade relations, as suggested by Rose (2016, 2019). Conversely, China may strategically reduce trade exposure to areas where anti-China sentiment is prevalent, aiming to avoid reinforcing negative perceptions or to apply soft economic pressure (Eichenauer et al., 2021). These dynamics imply that import patterns could be both a cause and a consequence of

[7] Table 8 provides the descriptive statistics. Education is measured categorically, specifying if the respondent has received 1-8 years of education, 8-15 years of education, or 15 or more years. *Urban* is assigned values based on the respondent's residence: one if the respondent lives in a rural area or village, two if they live in a small town, three if they live in the suburb of a large city, and four if they live in a large city.

[8] The main results remains robust to clustering at the level of region-year, country, and country-year.

public opinion, complicating causal interpretation.

To address these concerns, we follow Autor et al. (2013) and deploy an empirical strategy that isolates plausibly exogenous variation in local exposure to increased imports from China—the "China shock." The intuition of this approach is to use the surge in Chinese exports in the aftermath of WTO accession in 2001 as a quasi-exogenous supply-side shock to the global trading environment that is independent of the conditions in the importing countries. China's WTO accession was accompanied by a set of domestic economic reforms emphasizing market orientation and trade liberalization, which led to the way for the country to become the largest exporter of manufacturing goods. We follow Autor et al. (2013) and interact the Chinese import shock with the initial manufacturing employment shares in a local labor market, creating a shift-share design for the region-specific exposure to the China shock. This measure has the following intuition: For given changes in country-level manufacturing imports per worker, the treatment exposure will be stronger in those regions in which the manufacturing employment shares were initially higher and where larger increases in imports from China occurred. It will thus take larger values in regions with higher initial manufacturing employment and for which the change in imports from China has been stronger.

Formally, the import shock looks as follows:

$$Import\,Shock_{crt} = \frac{L_{crk,\,2000}}{L_{cr,\,2000}} \times \frac{\Delta IMP\,China_{ct}}{L_{c,\,2000}} \tag{2}$$

where the initial manufacturing employment share from the base year 2000 $\frac{L_{crk,\,2000}}{L_{cr,\,2000}}$ in each region is given by the share of workers of region r in country c employed in manufacturing (k), which captures the relative importance of the manufacturing sector k for a region r.[9] Regional manufacturing employment shares are sourced from Minnesota Population Center (2022).[10]

The local manufacturing share in 2000, $\frac{L_{crk,\,2000}}{L_{cr,\,2000}}$, is interacted with $\Delta IMP\,China_{ct}$, which denotes the change in import demand from country c for manufacturing goods from China. We

[9]This approach follows Colantone and Stanig (2018b) in using a single manufacturing employment share. We chose the year 2000 as it is the last year before China's accession to the WTO. Manufacturing shares for the year 2000 are not available for all countries in our sample. Where this is not the case, we select data that is closest to the year 2000. Column 2 of Table 6 depicts the exact year of the data sourced for each country in the sample.

[10]We use the INDGEN-variable (`https://international.ipums.org/international-action/variables/INDGEN#description_section`) for calculating manufacturing employment shares and the GEOLEV1-variable (`https://international.ipums.org/international-action/variables/GEOLEV1#description_section`) as the regional identifier. The INDGEN-variable is available for 25 African countries and contains information from census data in which industry a respondent works. Responses labeled as "Not in universe" are omitted following Baccini et al. (2021). To ensure national representativeness, we employ the population weights (PERWT) variable. As Minnesota Population Center (2022) uses different geographical units than ADM1, we harmonize the data by means of a spatial match that takes the overlap of the geographical areas used by Minnesota Population Center (2022) and ADM1 into account. Figure 2 visualizes the manufacturing employment shares across ADM1 regions.

follow Colantone and Stanig (2018b) and use the first-differences of imports lagged by one year (equivalent to t_{-2} minus t_{-1}) to allow for any public opinion affects to accrue over time.[11]

A challenge in estimating the impact of Chinese imports is that observed import flows may be correlated with demand shocks in the importing country. If rising African imports from China reflect not only China's growing export capacity but also increasing demand for particular goods, then a simple OLS estimate may understate the true effect of trade exposure on soft power in African economies, since both soft power and imports could be jointly influenced by unobserved demand factors.

To isolate the causal impact of import competition from China, we leverage the fact that much of the import growth during the period was driven by supply-side forces in China—such as improvements in productivity, trade liberalization, the dismantling of central planning, and China's accession to the WTO—rather than by changes in local demand. We therefore follow Autor et al. (2013), Colantone and Stanig (2018b), and Milner (2018) and instrument $Import\,Shock_{crt}$ using the influx of Chinese manufacturing goods to comparable countries. Specifically, we group the countries in our sample into low-income, lower-middle-income and upper-middle-income countries based on the World Bank's 2000 classification (World Bank, 2023a). Subsequently, we use the manufacturing exports from China to countries outside Africa, which are categorized within these three income groups, as instruments. This approach effectively treats import flows as exogenous and specific to each country's income group.[12] We use the following specification for our instrument:

$$Import\,Shock\_z_{crt} = \frac{L_{crk,\,2000}}{L_{cr,\,2000}} \times \frac{\Delta IMP\,China_{\,WB.Inc-Africa_t}}{L_{WB.Inc-Africa,\,2000}} \tag{3}$$

Here, African countries' manufacturing imports from China ($\Delta IMP\,China_{ct}$) are instrumented with $\Delta IMP\,China_{\,WB.Inc-Africa_t}$—the time-variant change in manufacturing imports from China across 26 low-income, 40 lower-middle-income and 24 upper-middle-income countries outside Africa.[13] We opted for this income group-specific approach, as these countries should exhibit similar import structures as their African counterparts, and thereby follow Autor et al. (2013), who build the import shock measure for the US based on other high-income countries.

A second deviation from Equation 2 is the denominator, which requires manufacturing employment data from the same set of income-specific countries outside Africa as in the numerator. Given the absence of aggregate sectoral employment data for these 90 countries, we approxi-

[11]We focus on a one year lag as respondents likely have only short recall periods for economic supply shocks.
[12]The shift component of the instrument therefore varies only by country-income group, not by individual country.
[13]For a comprehensive list of the countries used to construct the instrument, refer to Table 6.

mate their total manufacturing employment through the following steps: First, we calculate the total active labor force participation using data from World Bank (2023b) and accounting for unemployment based on World Bank (2023c). Second, we derive manufacturing employment shares from the base year 2000 for the three income groups using a subset out of 24 of the 90 countries used for the instrumented trade flows with data sourced from the Economic Transformation Database (ETD) (de Vries et al., 2021).[14] We then multiply these manufacturing employment shares with the total labor force for the subsets of countries outside Africa in the three income groups. We therefore obtain a proxied measure of the total number of workers in the manufacturing sector for each income category ($L_{WB.Inc-Africa,2000}$). This procedure aims to ensure the exogeneity of shares and eventually of the $Import\,Shock\_z_{crt}$. Finally, the import shock is uniformly expressed in thousands USD per worker.

We therefore estimate the following Two-Stage-Least Squares (2SLS) regression, which aims to provide causal estimates. In Equation 1, we replace $Import\,Shock_{crt}$ with the fitted values of $\widehat{Import\,Shock}_{crt}$.[15] Summing up, the corresponding first-stage regression looks as follows,

$$Import\,Shock_{crt} = \beta Import\,Shock\_z_{crt} + \tilde{\sigma}X_{jt} + \tilde{\theta}_{ct} + \tilde{\mu}_r + \tilde{\epsilon}_{cr} \tag{4}$$

where the notation from the earlier equations remains valid. The corresponding second-stage regression is then defined as follows,

$$Approval\ of\ China_{jcrt} = \beta_1 \widehat{Import\,Shock}_{crt} + \sigma X_{jt} + \theta_{ct} + \mu_r + \epsilon_{cr} \tag{5}$$

where $\widehat{Import\,Shock}_{crt}$ refers to the fitted (and instrumented) treatment values of $Import\,Shock_{crt}$, as derived from the first-stage regressions. This identification strategy captures the part of the variation in African imports from China that is linked to exogenous supply-side conditions in China, which are distinct from any demand-side factors sides the African countries that could simultaneously affect African approval rates of China, following the logic of Autor et al. (2013). We discuss the results of these regressions in the following section.

[14] Appendix Table 7 highlights this subset with bold markings.

[15] One could also think of it as $Import\,Shock\_z_{crt}$.

4 Results

4.1 Baseline Results

Table 1 displays the baseline estimates of Equation 1 for the *Approval of China* at the individual level with increasingly stricter sets of fixed effects. To hold coefficient interpretation as simple as possible, we employ a linear probability model (LPM).[16] Panel A reports the OLS regressions results, where the import shock is defined as in Equation 2. Panel B yields the IV results with the import shock being instrumented following Equation 3. Panel C reports corresponding first-stage regression results.[17]

Transitioning to the analysis, we begin with a parsimonious model that does not incorporate fixed effects (column 1). The OLS results showcase an insignificant negative coefficient. With stricter sets of fixed effects, the negative coefficient increases slightly and is statistically significant at the 1-percent level in our preferred specification (see Equation 1) in column 3.

Table 1: Individual level results: Baseline

	(1)	(2)	(3)
	Panel A: OLS		
Import Shock	-0.0101	-0.0626^{*}	-0.1030^{***}
	(0.0152)	(0.0337)	(0.0301)
	Panel B: 2SLS		
Import Shock	-0.4633^{***}	0.2733	0.3045
	(0.0742)	(0.1882)	(0.2091)
	Panel C: First stage		
Import Shock	0.4310^{***}	0.7144^{***}	0.6483^{***}
	(0.0931)	(0.1033)	(0.1070)
Observations	133,726	133,726	133,726
Number of Countries	22	22	22
Number of ADM1 regions	261	261	261
Country-Year FE		✓	✓
ADM1 FE			✓
Kleibergen-Paap F-Stat	58.5	135.3	72.6

Notes: The dependent variable in panels A-B is *Approval of China* as explained in Section 3. In Panel C, the dependent variable, and in Panel A-B, the main explanatory variable is the import shock instrumented using Chinese exports to other low-income, lower-middle income and upper-middle income countries outside of Africa, as outlined in Equation 3. We include the control variables age, age^2, gender, education, and urban in all specifications. Standard errors are in parentheses and clustered at ADM1-level. Significance levels: $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$.

[16] Using probit produces similar results.

[17] Please note that we take into account the individual weights specified by the *wgt* variable in the GWP. Refer to Table 14 for the baseline estimates without these weights.

Turning to the first stage of the IV estimates, we find the expected positive and significant correlation between the instrumental variable and the country-level manufacturing imports from China. The first-stage Kleibergen-Paap Wald rk F-statistic is above the widely accepted benchmark of 10 across the board. This supports the validity of the instrument. The coefficients are substantially higher compared to the corresponding OLS estimates. The differences in magnitude and the change in sign of the IV estimates may suggest the presence of endogeneity bias in the OLS model, possibly due to omitted variables that are correlated with both increased manufacturing imports from China and a heightened propensity of approving the Chinese leadership. This underlines the necessity for employing instrumental variables.

The average null finding of Chinese import competition on attitudes may still be subject to several mechanisms at play that level each other out. Therefore, we will delve into possible mechanisms in the next subsection.

4.2 Testing Mechanisms

Prevailing literature suggests multiple channels of how import competition may shape individuals' perceptions of their countries' trading partners. We test several of these mechanisms by substituting the dependent variable in the 2SLS model in Equation 1 with possible intermediary outcomes inherent in the GWP. Table 2 reports the individual-level regression results.

First, Autor et al. (2013) suggest that the China shock affects the labor market via its effect on income and wages. Mohan (2013) notes that for Sino-African economic relations, the effect on local labor markets is ambiguous. We start by analyzing the effect on income using self-reported per capita annual income in international dollars. As Fuchs et al. (2023), we winsorize $Income$ one-sided at the 99-percent level and then logarithmize it. Column 2 narrows the sample to individuals who work at least part-time to approximate the effect on workers' wages ($Wage\,Proxy$). To test for trade-induced poverty reduction and inequality effects, we include $Extreme\,Poverty$ in column 3 which is coded as 1 if an individual's income falls beneath the World Bank's poverty threshold of 2.15 USD per day (Fuchs et al., 2023).[18] In addition, we add the variable $Perceived\,Income$ ranging from 1 to 4 with lower values signaling economic hardship. Together, these four variables should help assess the mechanism on individual material well-being.[19] The results in columns 1-4 do suggest a general notion that manufacturing import competition did not improve individual material well-being, however $Perceived\,Income$ tends

[18]This equals a per-capita annual income of 785 USD.

[19]See Appendix D for detailed variable description.

to have improved following Chinese import competition.[20] The coefficient for *Living Standard* equals zero, indicating no observed change in living standards. Cumulatively, the estimated coefficients concerning an individual's material well-being in columns 1 to 5 lack consistency and robustness. While *Perceived Income* tends to improve following Chinese import shocks, the actual material well-being tends to remain unaffected. Overall, these findings do not contradict the null effect identified in Table 1.

Second, international trade increases central government revenues through import duties and affects local government revenues by changes in employment and firm activity (Feler and Senses, 2017). Shifting government revenues result in differential provision of public goods. To proxy for the quality of public goods in the respondents' residential areas, we draw from the "Community Basics" Index which ranges from zero to one measuring respondents' contentment with education, healthcare, housing, water, air, roads and public transport.[21] The results in column 6 do not indicate a change in the respondents' likelihood to report satisfaction with their community's public amenities following manufacturing import shocks. Thus, there is no evidence of trade-induced enhancements in public services being a prominent channel.

Third, increasing economic activity with China might increase the adoption of corrupt business practices (Isaksson and Kotsadam, 2018; Tawiah et al., 2022) and consequently lead to negative opinions about China. Conversely, improved living standards could reduce individuals' propensity to engage in bribe payments. The estimated coefficients in column 7 of Table 2 fall short of establishing a robust link between import shocks and reported corruption within businesses.

[20] Note that results are essentially unchanged when using an indicator variable *Median Income* instead of *Extreme Poverty* since about half (52.5%) of the respondents report incomes below the World Bank Poverty line.

[21] See Appendix D for detailed variable description. This channel and the preceding ones were also investigated in a different setting in Wellner et al. (2025).

Table 2: Testing potential mechanisms

	(1) Income	(2) Wage Proxy	(3) Extreme Poverty	(4) Perceived Income	(5) Living Standard	(6) Community Basics	(7) Corruption	(8) Migration	(9) Own Government Approval
Import Shock	-0.3166	0.9275	0.1783	0.8968*	-0.1881	0.1586	0.0943	0.4839*	0.2563
	(0.6609)	(0.7198)	(0.1890)	(0.5282)	(0.2337)	(0.1733)	(0.1956)	(0.2769)	(0.2528)
Observations	119,859	69,623	119,859	131,216	131,103	128,670	124,945	127,337	121,546
Number of Countries	22	22	22	22	22	22	22	22	21
Number of ADM1 regions	261	261	261	261	261	261	261	261	249
Mean of dependent variable	6.417	6.509	0.512	2.310	0.467	0.502	0.792	0.677	0.545
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
ADM1 FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Kleibergen-Paap F-Stat	35.8	22.9	36.9	35.8	36.6	34.5	37.3	34.4	33.8

Note: This table displays the regression results of Panel B of Table 1. *Approval of China* is substituted by intermediary outcomes as specified in the column header. Detailed variable descriptions are provided in Appendix D. We include the control variables age, age^2, gender, education, and urban in all specifications. Standard errors are in parentheses and clustered by ADM1 region. Significance levels: $^{*}\, p < 0.1$; $^{**}\, p < 0.05$; $^{***}\, p < 0.01$.

Fourth, other studies have attached importance to immigration attitudes when studying the effect of Chinese import competition on political outcomes (Colantone and Stanig, 2018a; Ferrara, 2023). The former suggests that higher levels of import competition are associated with anti-immigration attitudes, which eventually correlates with pro-Brexit voting. In the African context, this dynamic becomes particularly intriguing given the well-documented influx of Chinese labor accompanying Chinese development projects (Cervellati et al., 2022), which are also associated with more imports from China (Harchaoui et al., 2021). To the extent that development projects also entail the imports of input materials from China, it is conceivable that there might be heightened resentment toward foreign, especially Chinese, laborers, influencing perceptions of China. To test this link, we regress the right part of Equation 1 on a binary variable equal to 1 if the respondent believes their area is a good place for immigrants. However, we do not observe an increase in anti-immigrant sentiments following Chinese manufacturing import shocks. Even more, the coefficient is positive and statistically significant at least at the 10-percent level.

Finally, the China shock may also influence citizens' satisfaction with their own national government. In industrialized countries, this often leads to a tilt toward nationalistic or populist sentiments (Colantone and Stanig, 2018a; Dippel et al., 2022; Steiner and Harms, 2021). In the African context, we assume that import competition is perceived less as a sign of economic decline and more as a case of "premature deindustrialization" — that is, the foregone potential industrial growth rather than a tangible economic contraction (Rodrik, 2016). We therefore change the regressand to gauge approval for the national government.[22] The coefficient in column 9 indicates that the manufacturing import shocks may not have been strong enough to alter national political preferences. Albeit insignificant, the coefficient is comparable in size with those in Table 1. Taking the findings from Wellner et al. (2025) into consideration, this could indicate that Chinese development projects have a stronger influence on domestic approval ratings for African governments than Chinese manufacturing imports.

In summary, the impact of manufacturing import competition from China on intermediary outcomes, which may act as conduits for soft power effects, is both directionally ambiguous and limited in magnitude. These findings are therefore consistent with the null results of Table 1. This also resonates with Rudra et al. (2021), who posits that citizens in the developing world might have intricate anticipations concerning trade and globalization potentially blurring the lines between the actual repercussions of import competition from economic powers such as China and their expectations thereof.

[22]See Appendix D for detailed variable description.

4.3 Heterogeneity Analysis

This section continues uncovering heterogeneities of the China shock across several dimensions that may be hidden in the average effects of Table 1. We start with how the import shock varies across regional and country-level characteristics. To do so, we apply the model from column 3 in Table 1 to different sets of countries and regions in Table 3. The first such subset of countries is *Democracy History* indicating if the country of a respondent can be considered as a pre-treatment democracy based on the regime data by Bjørnskov and Rode (2020). It is plausible that Chinese foreign policy may have differential effects on attitude formation toward China across democratic and autocratic governance systems (Bader, 2015). *Technology Intensity* distinguishes countries based on whether they are medium- and high-tech technology manufacturing producers relative to the other countries in the sample (UNIDO, 2023). Although this paper focuses on import competition, we argue that individuals living in countries with higher technology intensity could develop different attitudes toward China in the wake of manufacturing import shocks. This aims to proxy the potentially varying degrees of industry competition in the manufacturing sector arising from import competition which in turn could yield different effects on employment, wages and ultimately, soft power.[23] Beijing underlines its consistent commitment to Africa through a diplomatic tradition dating back to the late 1980s whereby the foreign minister's first trip abroad each year is dedicated to visiting the African continent. The data by Wang and Stone (2022) allow to include a dichotomous variable (*China Leader Visit*) indicating whether a country received a high-level visit by a Chinese president or premier during the sample period. Previous studies documented trade promotional effects of state visits paid by high-level Chinese leaders (Beaulieu et al., 2020) as well as their efficacy in cultivating soft power (Goldsmith et al., 2021; Trunkos, 2021). *China Strategic Partner* allows to evaluate the potentially differential effects of the manufacturing import shock on residents of countries with which China has established strategic partnerships before or during the sample period (Strüver, 2017).

We also analyze heterogeneity across ADM1 regions within a country. For ADM1 regions that are the birthplace of at least one country leader during the sample period, the *Leader Birth Region* variable is assigned a value of one (Bomprezzi et al., 2024). This is expected to capture potential regional favoritism. Furthermore, China's approach to engaging with conflict-prone states contrasts with Western liberal democracies like the EU (Campbell et al., 2012). Such a difference inspires the examination of heterogeneity in the impact of manufacturing import shocks on

[23] See Appendix D for detailed variable description.

soft power among conflict-prone ADM1 regions. Specifically, a *Conflict* is defined as an event that invoked five or more casualties using the geo-referenced data by Sundberg and Melander (2013). Finally, we look at potential differential effects across *Capital Regions*.[24] The results from Table 3 reveal some notable disparities.

First, the relationship between the Chinese *Import Shock* and *Approval of China* is significantly different depending on whether a respondent lives in a democratic or autocratic country. Respondents residing in democratic countries are more likely to develop positive attitudes toward China. This positive effect might seem surprising at first glance. Yet, there may exist a selection mechanism where China seeks closer economic ties with the opposed political system in countries with lower baseline levels of public support to improve its image (Luongo, 2020).

Second, column 2 reveals that China may be able to increase its soft power via its manufacturing exports in countries with a relatively low *Technology Intensity* compared to the other countries in the sample. This coefficient is significant at the 5-percent level.

Third, individuals seem to value Chinese imports more, if the Chinese president or premier previously paid a visit to the country (suggested by the increased probability of respondents approving the Chinese leadership following the China shock in column 4). This effect could correspond to increased salience of Chinese soft power after leader visits, in line with existing evidence by Beaulieu et al. (2020) and Goldsmith et al. (2021).

China's ability to generate soft power via manufacturing exports seems to be less pronounced in capital regions as evidenced by column 6.[25] Lastly, the effect of the China shock is independent of whether a respondent resides in a strategic partner country of China.

[24] See Appendix D for detailed variable description.

[25] Note that for the calculation of the *Capital Region* heterogeneity, we used interaction terms, as we could not calculate the coefficient of interest due to collinearity when using sample splits.

Table 3: Heterogeneity analysis, sample splits

	(1) Democracy History	(2) Technology Intensity	(3) Leader Birth Region	(4) China Leader Visit	(5) Conflict	(6) Capital Region	(7) China Strategic Partner
Indicator = 0	0.1731	0.6125**	0.1532	−0.5562	0.2338	0.2694	0.1718
	(0.2196)	(0.2739)	(0.3102)	(0.4762)	(0.2131)	(0.1802)	(0.2884)
Indicator = 1	0.9829*	0.4114	0.1874	0.4388*	0.8663	−0.0682*	0.4485
	(0.5243)	(0.3522)	(0.4155)	(0.2226)	(1.298)	(0.0413)	(0.3125)
Observations	131,467	92,144	133,726	133,726	133,726	133,726	133,726
Number of Countries	22	13	22	22	22	22	22
Number of ADM1 regions	261	183	261	261	261	261	261
Country-Year FE	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓	✓

Note: Each cell of this table is a separate regression where we split the estimation sample by indicator variables, as specified by the column titles. Results corresponding to an indicator value of 0 are presented in the first row, whereas those corresponding to an indicator value of 1 are reported in the second row. The dependent variable is *Approval of China* as explained in Section 3. All interaction variables, except *Technology Intensity* are coded time-invariant. The coefficients of *Capital Region* are derived from an interaction model, given that the coefficient of interest was omitted due to collinearity in the subset where the capital region indicator equaled 1. We include the control variables age, age^2, gender, education, and urban in all specifications. Standard errors are in parentheses and clustered by ADM1 region. Significance levels: $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$.

The China shock is likely to affect soft power asymmetrically in different strata of the respondents. For this reason, we continue the heterogeneity analysis at the micro-level by interacting the import shock from column 3 from Table 1 with different labor market and income statuses (Colantone and Stanig, 2018a,b). An important observation is that the linear term for the manufacturing import shock in Table 4 remains consistent in magnitude, mirroring the baseline model results from column 3 in Equation 1. Additionally, the interaction terms are statistically insignificant across different subgroups of the labor market (columns 1 to 4). This implies that the null effect is independent of an individuals' employment status and income level. By and large, the results from Table 4 imply that the China shock yields a zero effect on *Approval of China* irrespective of respondents' employment status and income. This aligns with the results in Table 2 and indicates that income and wages neither act as mediators or moderators of a "China shock" on public opinion.

Table 4: Heterogeneity analysis, interaction terms: Micro

	(1) Full-time Employed	(2) Self Employed	(3) Unemployed	(4) Extreme Poverty
Import Shock	0.2420	0.2176	0.2769	0.2444
	(0.2083)	(0.2055)	(0.2095)	(0.1914)
Import Shock×Interaction	−0.0077	−0.0297	−0.0186	−0.0641
	(0.0154)	(0.0300)	(0.0148)	(0.0682)
Observations	133,726	133,726	133,726	119,859
R-squared	0.106	0.106	0.106	0.112
Country-Year FE	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Kleibergen-Paap F-Stat	14.7	14.4	12.5	22.7

Note: The dependent variable is *Approval of China* as explained in Section 3. Each column name denotes the interaction term used in the respective model and the second row in each Panel gives the respective coefficient. We include the control variables age, age^2, gender, education, and urban in all specifications. Standard errors are in parentheses and clustered by ADM1 region. Significance levels: $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$.

4.4 Robustness Checks

In Table 5, we conduct several robustness checks for the baseline IV specification in column 3 in Table 1. To mitigate endogeneity concerns, we begin by narrowing our sample to countries whose initial manufacturing employment data – used for constructing the instrument (see Equation 2) – originated between 1995 and 2005. This approach addresses the issue that more recent data for initial shares are more likely to correlate with contemporary shocks, potentially biasing the analysis. Indeed, this procedure yields 2SLS results that are statistically significant at the 5-percent level. This suggests that it is vital for the import shock exposure metric that the employment shares measure ex-ante manufacturing concentration of a region. In column 2, we exclude South Africa from the sample given its status as the most advanced manufacturer in Africa. The coefficient remains unchanged in magnitude and statistical significance. In column 3, we vary the lag structure of the change in manufacturing imports to lagged second-differences.[26] In this case, the coefficient for China becomes smaller in magnitude but remains insignificant indicating some sensitivity of the results to the chosen lag structure.

Next, we consider export shocks which are calculated analogously to the import shocks. This adjustment operates on the assumption that African manufacturing exports are demand-driven following China's assimilation into the global economy pursuant to its WTO accession. The coefficient for a Chinese manufacturing export shock is positive and statistically significant at the 5-percent level indicating respondents' attitudes may be more sensitive to their country's exports to China rather than imports. In column 5, we present the reduced-form OLS estimate, where we directly regress $Approval\,of\,China$ on the instrumental variable. The coefficient and significance level of the reduced-form effect is consistent with the baseline IV estimates in column 3 in Table 1 reinforcing the credibility of the adopted identification strategy. As a further robustness check, we change the definition of the dependent variable in column 6 and code "Don't know" and "Refused" answers as the same category as "Disapprove". This approach yields around 50,000 observations more and reduces the magnitude of the coefficients as expected. The main result remains a null finding. Lastly, we change the definition of the import shock and its instrument in column 7.[27] Instead of employing initial manufacturing employment shares as the regional weights in Equation 2 and Equation 3, we use urbanization rates calculated from the World Settlement Footprint 2015 data by Marconcini et al. (2020).[28] If the result with urbanization shares aligns closely with that using manufacturing employment shares, it would question the validity of the employment channel as an identification strategy. Turning to the result in column 7 of Table 5, the coefficient remains statistically insignificant; however, its increased magnitude does not provide definitive support for the labor market mechanism.

[26] To illustrate this, an import shock in 2010 would then be based on the change in manufacturing imports between the 2009 and 2007 value.

[27] This is the left part of Equation 2 and Equation 3.

[28] Considering that the range of the derived values is narrower than the initial manufacturing employment shares, we adjust the urbanization values with min-max normalization.

Table 5: Individual level estimates: Robustness

	(1) Shares 2000 strict	(2) Without South Africa	(3) Lagged-second differences	(4) Export Shock	(5) Reduced-form	(6) Alternative Dep. Variable	(7) Urbanization Share
Import Shock: 2SLS	0.4370^{**}	0.3003	0.1176	0.3945^{**}	-	0.2611	0.4717
	(0.2095)	(0.2815)	(0.1604)	(0.1632)		(0.2380)	(0.3085)
Import Shock: OLS	0.1429	-0.1036^{***}	-0.0686^{***}	0.0037	0.1974	-0.0987^{***}	0.0061
	(0.1034)	(0.0299)	(0.0210)	(0.0303)	(0.1327)	(0.0343)	(0.0239)
Observations	90,724	122,838	133,260	133,726	133,726	183,737	133,726
Number of Countries	13	21	22	22	22	22	22
Number of ADM1 regions	165	252	261	261	261	261	261
Country-Year FE	✓	✓	✓	✓	✓	✓	✓
ADM1 FE	✓	✓	✓	✓	✓	✓	✓
Kleibergen-Paap F-Stat	27.4	24.8	16.5	6.31	-	36.5	9.31

Note: The dependent variable is *Approval of China* as explained in Section 3. Each column name denotes the type of robustness tests performed. We include the control variables age, age^2, gender, education, and urban in all specifications. Standard errors are in parentheses and clustered by ADM1 region. Significance levels: $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$.

5 Conclusion

This paper examines the impact of manufacturing imports from China on its soft power in Africa during the period of 2008 to 2020. To approach this question, we develop a regional measure of an import shock in Section 3 inspired by the China shock literature (e.g. Autor et al., 2013; Colantone and Stanig, 2018b; Milner, 2021). We merge this primary explanatory variable with repeated cross-sectional public opinion data from the Gallup World Poll covering 22 African countries and over 261 sub-national ADM1 regions.

China's rapid integration into the global economy after joining the WTO is also evident in its trade flows with Africa. We have outlined the competition and the input effect on African manufacturing, which are posited to have opposing implications for soft power. Unlike previous studies, we leverage the China shock intuition to measure local trade shocks in the African context to study its effect on soft power. Therefore, this paper addresses a gap in the literature by applying this method to study a micro-level outcome. The instrumental-variables strategy allows us to identify the causal effects of manufacturing imports on attitudes toward China over time. More specifically, we exploit exogenous variation in China's manufacturing exports across low-income, lower-middle-income and upper-middle-income countries outside of Africa to isolate the supply side of manufacturing exports to African countries.

Our results, however, do not suggest that the China shock significantly influences African citizens' attitudes on average. The ambiguous results of potential mechanisms such as the effects on individual material well-being seem to counterbalance the competition and the input effect and reinforce this null finding. Yet, within these average effects lie intriguing nuances. For instance, China witnesses some success in improving its image in democratic countries as a result of its manufacturing exports. The null result is robust to different labor market interactions, lag structure, variable definitions, as well as to a replication of the analysis with EU imports.

Overall, this paper enhances the literature by being the first to causally examine the soft power effects of the China shock in the African context. Our null result is consistent with findings from Latin America (Eichenauer et al., 2021). Taken together, this may indicate that the China shock is less pronounced in the developing world than in the US and Western Europe, and therefore has less impact on individual attitudes via the competition effect. We find no evidence of a reputational penalty associated with Chinese imports arising from competition-induced adjustments.

This paper can serve as a starting point for further studies exploring trade-related soft power effects in Africa. A major caveat of this paper remains the limited granularity of the manufacturing employment data, which impedes sub-sectoral analysis within manufacturing. Consequently, we rely on a less accurate measure with limited variation of the import shock compared to previous studies. Hence, our results should be treated with caution. Yet, future research can enhance our work by using more granular manufacturing employment data coupled with more detailed import data resulting in differently measured import shocks (e.g. Nedoncelle and Wolfersberger, 2023; Ngoma, 2023). It would also be interesting to distinguish import shocks based on their technology intensity following the OECD (2011) framework. Moreover, emphasis should be placed on further disentangling the competition and the input effects. Having data not only on the employment status of survey respondents, but also on the industries in which they work would allow for a more insightful picture.

It will be particularly interesting to observe whether the African Continental Free Trade Area (AfCFTA) advances Africa regional integration and enhances welfare, and how this affects trade relations with China and the EU. Moreover, the across-the-board tariff announcements made by the US in early 2025 may yield noteworthy implications for the evolution of trade-induced soft power dynamics. Country-specific case studies, particularly those focusing on countries with a stronger manufacturing base like South Africa, would be a valuable addition. Finally, while we do not find significant effects on the support for African countries' leadership, scrutinizing election outcomes as a dependent variable presents another promising avenue for research.

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Appendix A: Data

Table 6: List of countries in sample

Gallup World Poll	IPUMS	Sample for Analysis
Algeria		
Angola		
	Benin (2002)	
	Botswana (2001)	
Burkina Faso	Burkina Faso (1996)	Burkina Faso
Burundi		
Cameroon	Cameroon (2005)	Cameroon
Chad		
Central African Republic		
Comoros		
Cote d'Ivoire		
Djibouti		
Egypt	Egypt (1996)	Egypt
Ethiopia	Ethiopia (1994)	Ethiopia
Gabon		
Gambia		
Ghana	Ghana (2000)	Ghana
Guinea	Guinea (2014)	Guinea
Kenya		
Lesotho	Lesotho (2006)	Lesotho
Liberia	Liberia (2008)	Liberia
Madagascar		
Malawi	Malawi (1998)	Malawi
Mali	Mali (1998)	Mali
Mauritania		
Mauritius	Mauritius (2000)	Mauritius
Morocco	Morocco (2014)	Morocco
Mozambique	Mozambique (1997)	Mozambique
Namibia		
Niger		
Nigeria		
Republic of Congo		
Rwanda	Rwanda (2002)	Rwanda
Senegal	Senegal (2013)	Senegal
Sierra Leone	Sierra Leone (2004)	Sierra Leone
Somalia		
South Africa	South Africa (2001)	South Africa
South Sudan	South Sudan (2008)	South Sudan
Sudan	Sudan (2008)	Sudan
Swaziland		
Tanzania	Tanzania (2002)	Tanzania
Togo	Togo (2010)	Togo
Tunisia		
Zambia	Zambia (2000)	Zambia
Zimbabwe		

Notes: The table lists all countries for which it is possible to accurately map the sub-national identifiers available in Gallup (2020) and Minnesota Population Center (2022) to ADM1 regions (Hijmans et al., 2018). The years within brackets denote the specific years from which manufacturing employment data have been sourced. To qualify for regression analysis, data must be available in both data sets. Hence, the third column gives the sample of countries used in this study.

Table 7: Countries used for IV construction

low-income	lower-middle income	upper-middle income
Afghanistan	Albania	**Argentinia**
Armenia	Bulgaria	Bahrain
Azerbaijan	Bosnia and Herzegovina	**Brazil**
Bangladesh	Belarus	Barbados
Bhutan	Belize	**Chile**
Georgia	**Bolivia**	Czech Republic
Haiti	**Colombia**	Estonia
Indonesia	**Costa Rica**	Croatia
India	Cuba	Hungary
Kyrgyz Republic	Dominican Republic	**Korea, Rep.**
Cambodia	Fiji	Lebanon
Lao PDR	Guatemala	St. Lucia
Moldova	Guyana	**Mexico**
Myanmar	Honduras	Malta
Mongolia	Iran, Islamic Rep.	**Malaysia**
Nicaragua	Iraq	Oman
Nepal	Jamaica	Panama
Pakistan	Jordan	Poland
Korea, Dem. Rep.	Kazakhstan	Puerto Rico
Solomon Islands	**Sri Lanka**	Saudi Arabia
Tajikistan	Lithuania	Slovak Republic
Turkmenistan	Latvia	Trinidad and Tobago
Ukraine	Maldives	Uruguay
Uzbekistan	North Macedonia	Venezuela, RB
Vietnam	**Peru**	
Yemen, Rep.	**Philippines**	
	Papua New Guinea	
	Paraguay	
	West Bank and Gaza	
	Russian Federation	
	El Salvador	
	Suriname	
	Syrian Arab Republic	
	Thailand	
	Tonga	
	Türkiye	
	St Vincent and the Grenadines	
	Vanuatu	
	Samoa	
	Ecuador	

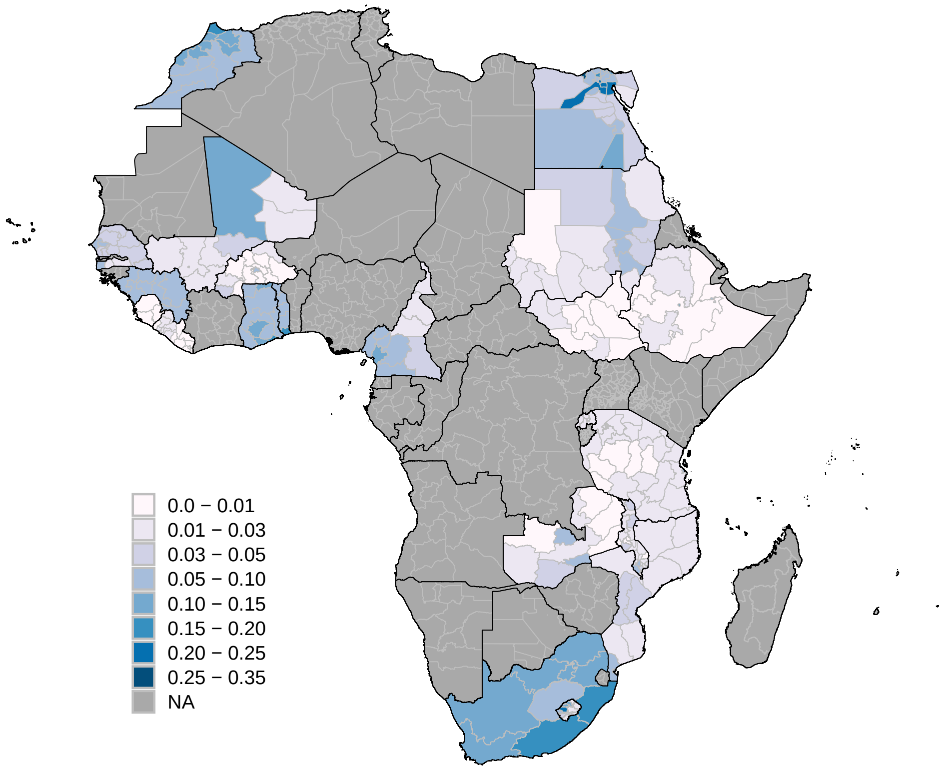
Notes: The table lists all countries whose trade data we use to instrument for African trade with China as in Equation 3. The income categories are defined according to the World Bank classification in the year 2000 (World Bank, 2023a). Countries highlighted in bold represent the subset upon which the manufacturing employment share proxies are predicated, using the data from de Vries et al. (2021).

Table 8: Descriptive statistics

	Obs	Mean	SD	Min	Max
Approval of China	140,638	0.730	0.444	0	1
China Import Shock	143,146	0.040	0.258	-1.667	2.745
Female	143,146	0.468	0.499	0	1
Age	142,819	33.845	14.729	13.000	99.000
Age squared	142,819	1,362.436	1,247.253	169.000	9,801.000
Education	142,585	1.593	0.616	1	3
Urban	136,784	2.154	1.056	1	4

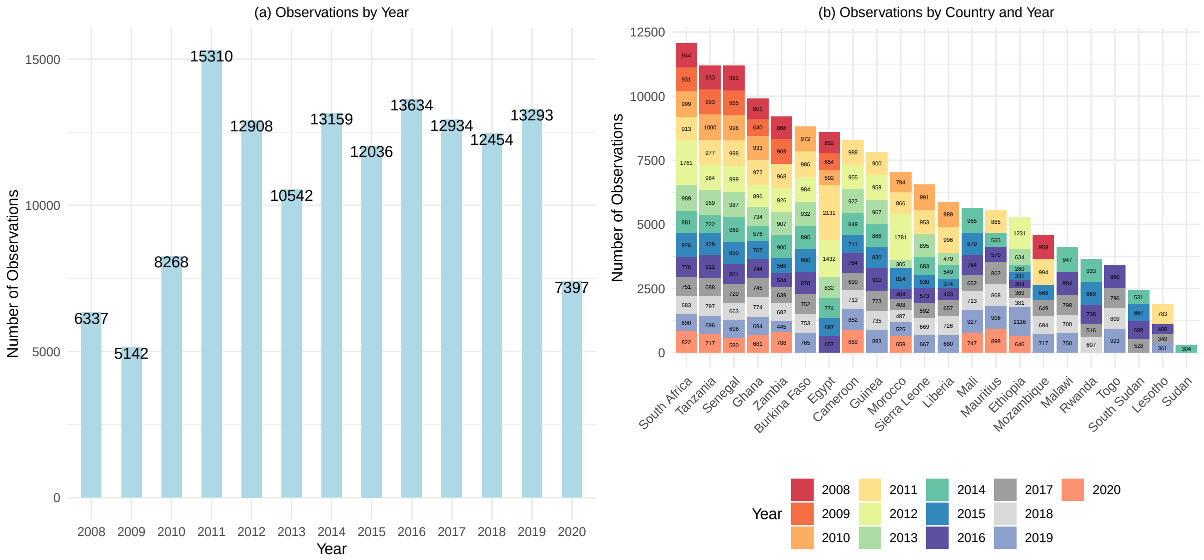
Notes: The table displays the descriptive statistics for the samples used in the analysis at individual level. It includes all observations from the GWP for which *Approval of China* is available.

Figure 2: Spatial variation in initial manufacturing employment shares (in percent) across ADM1 regions



Notes: This figure visualizes the initial manufacturing employment shares based on data by Minnesota Population Center (2022) across ADM1 regions in the 22 countries included in the sample. For all countries, the data was selected from the closest available year to 2000 (see Table 6).

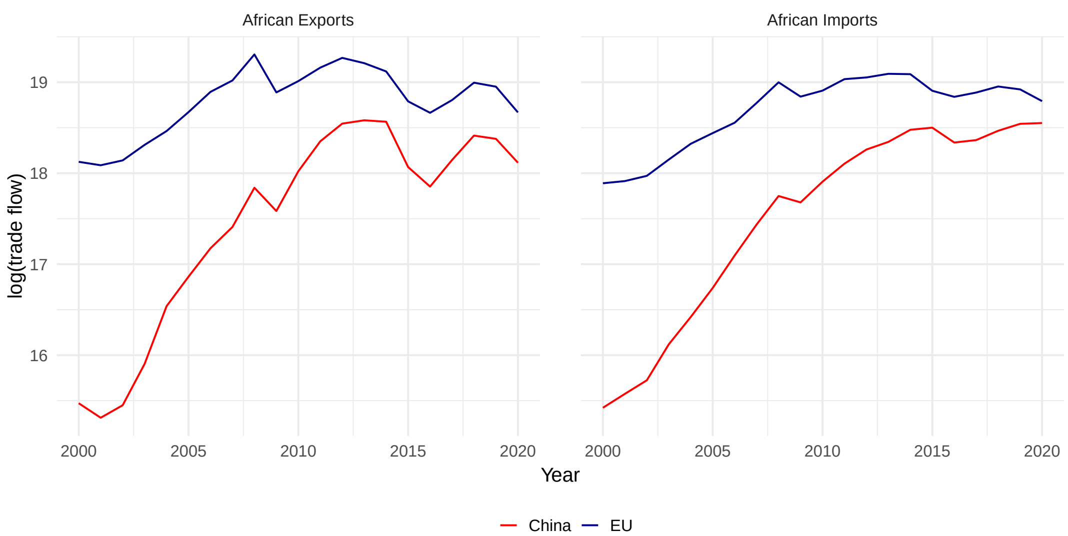
Figure 3: Distribution of GWP observations (2008-2020)



Notes: The figure provides an overview of the distribution of the 143,146 observations of the two outcome variables (*"Do you approve or disapprove of the job performance of the leadership of China?"*, and the EU (*"Do you approve or disapprove of the job performance of the leadership of the following countries? The European Union."*) excluding "Don't know" and "Refused" responses over surveyed years (Panel A) and by country and year (Panel B).

Appendix B: Comparative Results EU

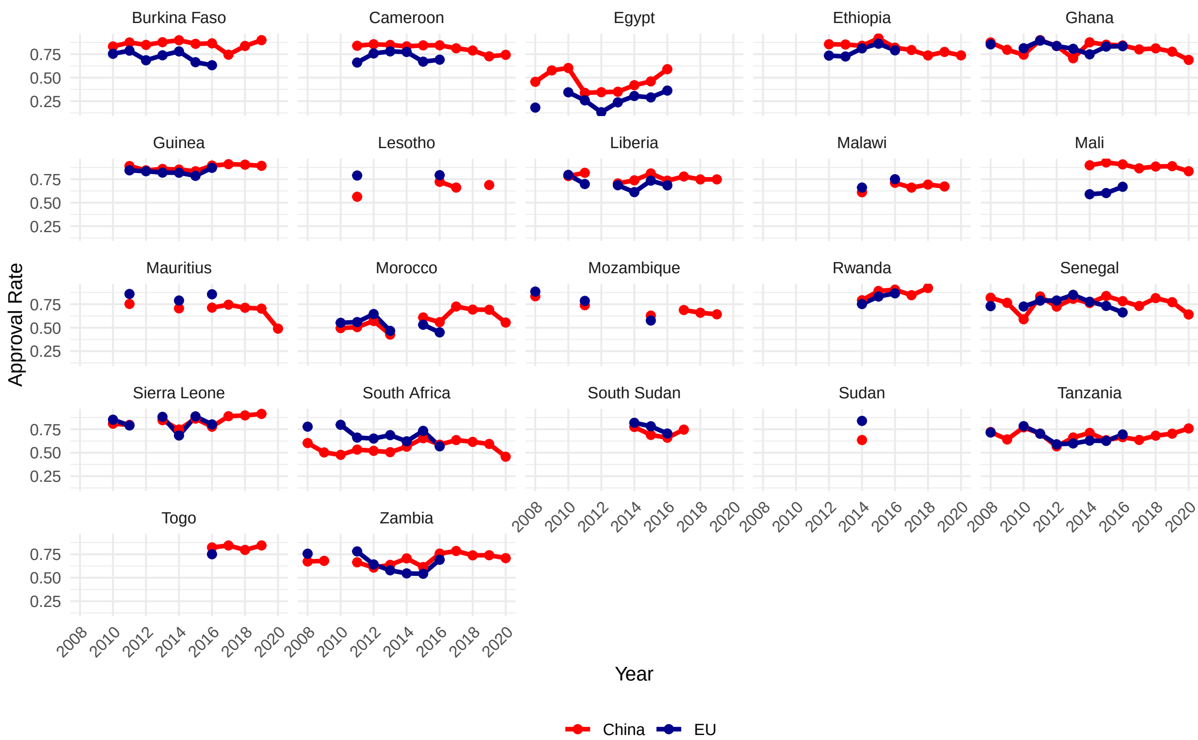
Figure 4: Overall trend in Sino-African and EU-African trade



Notes: The figure visualizes the logarithmised overall trade volumes in the manufacturing, agriculture and mineral sector between 2000 and 2020 between Africa and China (red) and the EU (blue).

To examine whether the null finding is peculiar to the China shock, we replicate the analysis for import competition from the EU. The information on the EU global import demand is also obtained from the World Integrated Trade Solutions (WITS) database provided by the World Bank (2022).[29] Analogously, we utilize the question *"Do you approve or disapprove of the job performance of the leadership of the following countries? The European Union."* from the GWP to construct the dependent variable for the EU's soft power. For the EU it yields 85,019 answers. As before, the answers "Don't know" and "Refused" are labelled as missing values and therefore omitted from the main analysis. This is the case for 5983 answers for the EU. For the EU, the countries with the highest mean approval rates are Sudan and Mauritius (both 84%) and with the lowest rate again the two Northern African countries of Egypt (25%) and Morocco (56%).[30]

Figure 5: Average support for China and the EU by country over time (2008-2020)

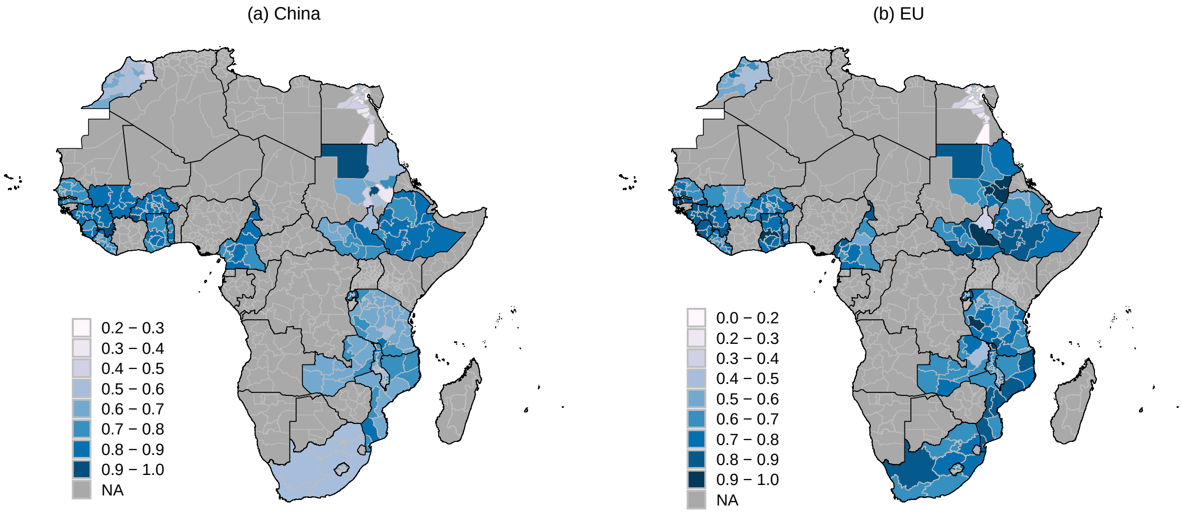


Notes: This figure extends Figure 1 by the respective EU soft power data from the GWP to enable a comparative perspective. Note that EU data is only available up to 2016.

[29]EU trade data is defined as the cumulative sum of two reporters in the WITS database: *EU28 - EU members (excl. UK) – EU-UK* and *United Kingdom – GBR*. Our decision to treat the UK as an integral part of the EU throughout the sample arises from its formal membership up until early 2020, and due to the EU soft power variable from the GWP being available solely up to 2016 – the year marking the Brexit referendum.

[30]See also Figure 6 for spatial variation in the mean approval rates by ADM1 region.

Figure 6: Spatial variation in average support for China and the EU (2008-2020 for China, 2008-2016 for EU)



Notes: The figure visualizes the average share of survey respondents that approve China and the EU by ADM1 region.

Table 9: Individual level results: Baseline EU

	(1)	(2)	(3)
	Panel A: OLS		
Import Shock EU	-0.0554^{***}	0.0005	-0.0030
	(0.0188)	(0.1011)	(0.1065)
	Panel B: 2SLS		
Import Shock EU	-0.0286	0.3055^{*}	0.2050
	(0.0219)	(0.1567)	(0.1350)
	Panel C: First stage		
Import Shock EU	0.8858^{***}	0.9805^{***}	1.034^{***}
	(0.1445)	(0.0976)	(0.0910)
Observations	79,423	79,423	79,423
Number of Countries	22	22	22
Number of ADM1 regions	258	258	258
Country-Year FE		✓	✓
ADM1 FE			✓
Kleibergen-Paap F-Stat	77.1	180.3	256.6

Notes: The dependent variable in panels A-B is *Approval of EU*. In Panel C, the dependent variable, and in Panel A-B, the main explanatory variable is the import shock instrumented using EU exports to other low-income, lower-middle income and upper-middle income countries outside of Africa, as outlined in Equation 3. We include the control variables age, age^2, gender, education, and urban in all specifications. Standard errors are in parentheses and clustered at ADM1-level. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 10: Testing potential mechanisms

	(1) Income	(2) Wage Proxy	(3) Extreme Poverty	(4) Perceived Income	(5) Living Standard	(6) Community Basics	(7) Corruption	(8) Migration	(9) Own Government Approval
Import Shock EU	-0.6156*	-0.1944	0.2267*	0.2115	-0.1053	0.0589	0.0828	0.3104**	0.0103
	(0.3450)	(0.4002)	(0.1320)	(0.3630)	(0.1278)	(0.0751)	(0.1708)	(0.1315)	(0.1380)
Observations	65,725	36,878	65,725	78,183	77,304	76,046	75,078	76,712	71,325
Number of Countries	22	22	22	22	22	22	22	22	21
Number of ADM1 regions	258	257	258	258	258	258	258	258	235
Mean of dependent variable	6.365	6.462	0.525	2.307	0.439	0.489	0.793	0.667	0.548
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
ADM1 FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Kleibergen-Paap F-Stat	107.4	67.1	129.8	107.4	202.8	187.6	132.5	133.3	90.3

Note: This table displays the regression results of Panel B of Table 9. The dependent variable is substituted by intermediary outcomes as specified in the column header. Detailed variable descriptions are provided in Appendix D. We include the control variables age, age^2, gender, education, and urban in all specifications. Standard errors are in parentheses and clustered by ADM1 region. Significance levels: $^{*}\, p < 0.1$; $^{**}\, p < 0.05$; $^{***}\, p < 0.01$.

Table 11: Heterogeneity analysis, sample splits: Macro

	(1) Democracy History	(2) Technology Intensity	(3) Leader Birth Region	(4) China Leader Visit	(5) EU Trade Agreement	(6) Conflict	(7) Capital Region	(8) China Strategic Partner
Indicator = 0	0.2129	−0.1860	−0.0101	2.851	0.3304	0.2540*	0.1379	1.380***
	(0.1383)	(0.4016)	(0.2511)	(1.990)	(0.3956)	(0.1399)	(0.1113)	(0.5036)
Indicator = 1	−0.0288	0.2834*	0.5299***	0.1813	0.1976	1.537***	−0.0984***	0.0129
	(0.6669)	(0.1578)	(0.1589)	(0.1346)	(0.1418)	(0.5148)	(0.0281)	(0.1253)
Number of Countries	22	13	22	22	22	22	22	22
Number of ADM1 regions	258	180	258	258	258	258	258	258
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓	✓	✓

Note: Each cell of this table is a separate regression where we split the estimation sample by indicator variables, as specified by the column titles. The results for when the indicator is 0 are shown in the first row, while results for when the indicator is 1 are displayed in the second row. The dependent variable is *Approval of EU*. All interaction variables, except *Technology Intensity* are coded time-invariant. The coefficients of *Capital Region* are derived from an interaction model, given that the coefficient of interest was omitted due to collinearity in the subset where the capital region indicator equaled 1. We include the control variables age, age^2, gender, education, and urban in all specifications. Standard errors are in parentheses and clustered by ADM1 region. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 12: Heterogeneity analysis, interaction terms: Micro

	(1) Full-time Employed	(2) Self Employed	(3) Unemployed	(4) Extreme Poverty
Import Shock EU	0.2093	0.2183	0.2042	0.2900^{*}
	(0.1326)	(0.1329)	(0.1339)	(0.1490)
Import Shock EU×Interaction	−0.0054	-0.0565^{***}	-0.0595^{*}	0.0104
	(0.0192)	(0.0209)	(0.0324)	(0.0239)
Observations	79,423	79,423	79,423	65,725
R-squared	0.133	0.133	0.133	0.142
Country-Year FE	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Kleibergen-Paap F-Stat	46.9	46.9	43.2	34.8

Note: The dependent variable is *Approval of EU*. Each column name denotes the interaction term used in the respective model and the second row in each Panel gives the respective coefficient. We include the control variables age, age^2, gender, education, and urban in all specifications. Standard errors are in parentheses and clustered by ADM1 region. Significance levels: $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$.

Table 13: Individual level estimates: Robustness

	(1) Shares 2000 strict	(2) Without South Africa	(3) Lagged-second differences	(4) Export Shock	(5) Reduced-form	(6) Alternative Dep. Variable	(7) Urbanization Share
Import Shock EU: 2SLS	0.3120**	0.4394	0.2133	0.2497	-	0.1216	0.0152
	(0.1577)	(0.3318)	(0.1476)	(0.1695)		(0.1571)	(0.1754)
Import ShockEU : OLS	0.0853	−0.0573	−0.0030	0.0450	0.2120	−0.0346	0.0393
	(0.1215)	(0.1395)	(0.0951)	(0.1056)	(0.1346)	(0.1066)	(0.0396)
Observations	54,718	72,605	78,841	79,423	79,423	108,671	79,423
Number of Countries	13	21	22	22	22	22	22
Number of ADM1 regions	164	249	258	258	258	258	258
Country-Year FE	✓	✓	✓	✓	✓	✓	✓
ADM1 FE	✓	✓	✓	✓	✓	✓	✓
Kleibergen-Paap F-Stat	93.3	26.2	37.3	158.0	-	90.6	6.61

Note: The dependent variable is *Approval of EU*. Each column name denotes the type of robustness tests performed. We include the control variables age, age^2, gender, education, and urban in all specifications. Standard errors are in parentheses and clustered by ADM1 region. Significance levels: $^{*}\, p < 0.1$; $^{**}\, p < 0.05$; $^{***}\, p < 0.01$.

Appendix C: Further Robustness Checks

Table 14: Individual level results: Baseline, no weights

	(1) China	(2) EU	(3) China	(4) EU	(5) China	(6) EU
			Panel A: OLS			
Import Shock	-0.0043	-0.0518^{**}	-0.0190	0.0092	-0.0547^{**}	0.0175
	(0.0155)	(0.0202)	(0.0297)	(0.0891)	(0.0277)	(0.0935)
			Panel B: 2SLS			
Import Shock	-0.4837^{***}	-0.0156	0.3531^{*}	0.3039^{**}	0.4723^{**}	0.2202^{*}
	(0.0843)	(0.0230)	(0.2075)	(0.1426)	(0.2080)	(0.1272)
Age	-0.0002	-0.0032^{***}	0.0012^{***}	-0.0011^{*}	0.0011^{**}	-0.0012^{**}
	(0.0006)	(0.0008)	(0.0004)	(0.0006)	(0.0004)	(0.0006)
Age^2	-3.88e-6	2.8e-5***	-9.76e-6**	9.81e-6	-9.16e-6*	1.06e-5
	(5.94e-6)	(8.09e-6)	(4.88e-6)	(6.88e-6)	(4.99e-6)	(6.67e-6)
Education	-0.0167^{**}	-0.0103	0.0211^{***}	0.0187^{***}	0.0208^{***}	0.0179^{***}
	(0.0071)	(0.0071)	(0.0039)	(0.0056)	(0.0039)	(0.0053)
Female	-0.0482^{***}	-0.0042	-0.0361^{***}	-0.0084^{*}	-0.0358^{***}	-0.0093^{**}
	(0.0033)	(0.0049)	(0.0030)	(0.0044)	(0.0030)	(0.0043)
Urban	0.0027	-0.0134^{*}	-0.0002	-0.0033	0.0019	0.0020
	(0.0056)	(0.0076)	(0.0022)	(0.0035)	(0.0023)	(0.0036)
			Panel C: First stage			
Import Shock$_z$	0.4284^{***}	0.8921^{***}	0.7273^{***}	0.9798^{***}	0.6652^{***}	1.034^{***}
	(0.0925)	(0.1408)	(0.1027)	(0.0945)	(0.1086)	(0.0873)
Observations	133,994	79,423	133,994	79,423	133,994	79,423
Number of Countries	22	22	22	22	22	22
Number of ADM1 regions	261	258	261	258	261	258
Country-Year FE			✓	✓	✓	✓
ADM1 FE					✓	✓
Kleibergen-Paap F-Stat	21.4	40.1	50.2	107.6	37.5	140.1

Notes: The dependent variable in panels A-B is the soft power variable for either China or the EU as explained in Section 3. In Panel C, the dependent variable, and in Panel A-B, the main explanatory variable is the import shock instrumented using Chinese and EU exports to other low-income, lower-middle income and upper-middle income countries outside of Africa, as outlined in Equation 3. We include the control variables age, age^2, gender, education, and urban in all specifications. Standard errors are in parentheses and clustered at ADM1 level. Significance levels: $^{*}\ p < 0.1$; $^{**}\ p < 0.05$; $^{***}\ p < 0.01$.

As a robustness check, we also estimate the following regression equation at the regional level:

$$Approval\ of\ China_{crt} = \beta_1 Import\,Shock_{crt} + \sum_j \sigma_j X^j_{crt} + \theta_{ct} + \mu_r + \epsilon_{cr} \tag{1}$$

where $Approval\ of\ China_{crt}$ is the weighted share of individuals living in ADM1 region r of country c that approve of the Chinese leadership in year t.[31] $Import\,Shock_{crt}$ is the lagged first-difference of Chinese manufacturing imports as defined in Equation 2. The j individual-

[31]To calculate mean values of any variables from the GWP, we use the weights variable (wgt) included for each respondent in the GWP in order to account for the representativeness of each observation.

level control variables $\sum_j \sigma_j X^j_{crt}$ previously introduced are averaged at the ADM1 level.[32]

Fixed effects and standard errors are employed analogously to the individual-level regression. Equation 1 thus relies on variation of the average attitudes within ADM1 regions in a country over time after adjustments for prevalent trends at the national level have been made. β_1 reflects the average effect of the $Import\,Shock_{crt}$ on the attitudinal support for China.

Table 15 displays the baseline results from Equation 1 for both China and the EU. The IV coefficients from the preferred specifications in columns 5 and 6 including country-year and ADM1 fixed effects are comparable in magnitude and direction to the results from the individual level regression (Table 1). Mirroring the individual-level regression, the coefficients in Panel B are higher than their OLS counterparts in Panel A. It is worth noting that OLS results sometimes diverge in direction and significance in the ADM1 level regression. The instrument remains relevant (Panel C) and valid according to the Kleibergen-Paap F-statistic, although F-statistics decrease compared to Table 1. This result is robust to dropping those ADM1 region-year observations with the least coverage of individual observations.[33] Overall, the ADM1 level results are consistent with the individual level results.

[32]For descriptive statistics at the ADM1 level, see Panel B in Table 8.

[33]Specifically, we run the same regression after removing those observations with fewer than ten respondents within an ADM1 region in a given year. See Table 16 for detailed results.

Table 15: ADM1 level results: Baseline

	(1) China	(2) EU	(3) China	(4) EU	(5) China	(6) EU
	Panel A: OLS					
Import Shock	0.0286^{*}	-0.0135	-0.0931^{**}	-0.0127	-0.1230^{***}	0.0309
	(0.0152)	(0.0333)	(0.0462)	(0.1493)	(0.0435)	(0.1603)
	Panel B: 2SLS					
Import Shock	0.0486	0.0581	0.4827	0.2521	0.5579	0.2419
	(0.1041)	(0.0429)	(0.3064)	(0.2162)	(0.3498)	(0.2116)
Age	-0.0020	0.0012	0.0063	0.0173^{*}	0.0068	0.0178
	(0.0063)	(0.0108)	(0.0060)	(0.0094)	(0.0064)	(0.0117)
Age2	-2.85e-5	-7.34e-5	-7.85e-5	-0.0003^{**}	-9.41e-5	-0.0003^{*}
	(7.36e-5)	(0.0001)	(6.86e-5)	(0.0001)	(7.31e-5)	(0.0001)
Education	-0.1576^{***}	-0.1446^{***}	0.0772^{***}	0.0438	0.0872^{***}	0.0538
	(0.0249)	(0.0383)	(0.0267)	(0.0374)	(0.0335)	(0.0551)
Female	-0.1262^{***}	0.1116^{*}	-0.1134^{***}	0.0166	-0.0996^{**}	-0.0309
	(0.0442)	(0.0667)	(0.0385)	(0.0571)	(0.0407)	(0.0664)
Urban	0.0233^{***}	-0.0152	-0.0067	-0.0084	0.0028	0.0086
	(0.0088)	(0.0128)	(0.0070)	(0.0094)	(0.0104)	(0.0161)
	Panel C: First Stage					
Import Shock	0.3783^{***}	0.6885^{***}	0.5553^{***}	0.8387^{***}	0.5070^{***}	0.8761^{***}
	(0.0687)	(0.1098)	(0.1425)	(0.1200)	(0.1259)	(0.1173)
Observations	2,041	1,205	2,041	1,205	2,041	1,205
Number of Countries	22	22	22	22	22	22
Number of ADM1 regions	261	258	261	258	261	258
Country-Year FE			✓	✓	✓	✓
ADM1 FE					✓	✓
Kleibergen-Paap F-Stat	30.4	39.3	15.2	48.8	16.2	55.8

Note: The dependent variable in panels A-B is *Approval of China* and *Approval of EU* as explained in 3. In Panel C, the dependent variable, and in Panel A-B, the main explanatory variable is the import shock instrumented using Chinese exports to other low-income, lower-middle income and upper-middle income countries outside of Africa, as outlined in Equation 3. We include the control variables age, age^2, gender, education, and urban in all specifications. Standard errors are in parentheses and clustered at ADM1 level. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 16: ADM1 level results: Baseline, robust

	(1) China	(2) EU	(3) China	(4) EU	(5) China	(6) EU
			Panel A: OLS			
Import Shock	0.0158	−0.0320	−0.0652	0.1037	-0.0942^{*}	0.1252
	(0.0128)	(0.0298)	(0.0549)	(0.1373)	(0.0546)	(0.1612)
			Panel B: 2SLS			
Import Shock	0.0671	0.0466	0.3872	0.2211	0.5600	0.1943
	(0.1078)	(0.0413)	(0.2820)	(0.2157)	(0.3427)	(0.1998)
Age	-0.0126^{**}	−0.0137	−0.0022	0.0080	−0.0050	0.0053
	(0.0056)	(0.0108)	(0.0047)	(0.0086)	(0.0051)	(0.0094)
Age2	8.24e-5	0.0001	1.14e-5	−0.0001	3.09e-5	−0.0001
	(6.69e-5)	(0.0001)	(5.7e-5)	(0.0001)	(6.02e-5)	(0.0001)
Education	-0.1642^{***}	-0.1326^{***}	0.0893^{***}	0.0732^{**}	0.0976^{***}	0.0931^{**}
	(0.0258)	(0.0401)	(0.0255)	(0.0323)	(0.0316)	(0.0457)
Female	-0.1170^{***}	0.1602^{**}	-0.0974^{**}	0.0139	-0.0960^{**}	0.0267
	(0.0435)	(0.0685)	(0.0382)	(0.0546)	(0.0409)	(0.0634)
Urban	0.0261^{***}	−0.0112	−0.0073	−0.0088	0.0018	0.0246^{*}
	(0.0087)	(0.0127)	(0.0071)	(0.0089)	(0.0106)	(0.0147)
			Panel C: First Stage			
Import Shock	0.3636^{***}	0.6909^{***}	0.5483^{***}	0.8423^{***}	0.5048^{***}	0.8719^{***}
	(0.0674)	(0.1098)	(0.1463)	(0.1220)	(0.1306)	(0.1194)
Observations	1,902	1,117	1,902	1,117	1,902	1,117
Number of Countries	22	22	22	22	22	22
Number of ADM1 regions	256	252	256	252	256	252
Country-Year FE			✓	✓	✓	✓
ADM1 FE					✓	✓
Kleibergen-Paap F-Stat	29.1	39.6	14.0	47.6	14.9	53.4

Note: This table is equivalent to Table 15, but only includes ADM1 region-year pairs that consist of at least 10 individual observations. This drops around 6.5% of observations. The dependent variable in panels A-B is *Approval of China* and *Approval of EU* as explained in Section 3. In Panel C, the dependent variable, and in Panel A-B, the main explanatory variable is the import shock instrumented using Chinese and EU exports to other low-income, lower-middle income and upper-middle income countries outside of Africa, as outlined in Equation 3. All specifications include the control variables age, age squared, gender, education, and urban residence. Standard errors, clustered at the ADM1 region level, are reported in parentheses below the coefficient estimates. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix D: Variable Description

- **Approval of China**: Binary variable equal to 1 if the individual approves of the leadership of China based on the question "Do you approve or disapprove of the job performance of the leadership of China?" *Source: Gallup (2020).*

- **Approval of EU**: Binary variable equal to 1 if the individual approves of the leadership of the EU based on the question "Do you approve or disapprove of the job performance of the leadership of the following countries? The European Union." *Source: Gallup (2020).*

- **Manufacturing Imports China**: Annual African manufacturing imports from China in 1000 USD. *Source: World Bank (2022).*

- **Manufacturing Imports EU**: Annual African manufacturing imports from EU in 1000 USD. *Source: World Bank (2022).*

- **Instrumented Manufacturing Imports China**: Annual manufacturing imports from country-income groups as of Table 7 from China in 1000 USD. *Source: World Bank (2022).*

- **Instrumented Manufacturing Imports EU**: Annual manufacturing imports from country-income groups as of Table 7 from EU in 1000 USD. *Source: World Bank (2022).*

- **Age**: Stated age of the respondent in years. *Source: Gallup (2020).*

- **Age^2**: Squared age of the respondent. *Source: Gallup (2020).*

- **Female**: Binary variable equal to 1 if the respondent is female. *Source: Gallup (2020).*

- **Education**: Respondent's educational attainment on a 3-point index from 1 to 3. A value of 1 indicates 1-8 years of schooling, a value of 2 indicates 8-15 years and a value of 3 indicates 15 years or more. *Source: Gallup (2020).*

- **Urban**: Index from 1 to 4 indicating the type of area the respondent is from. It assigns a value of 1 if the respondent resides in a rural area or village, a value of 2 if they live in a small town, a value of 3 if they are situated in a suburb of a large city, and a value of 4 if they inhabit a large city. *Source: Gallup (2020).*

- **Income**: Respondents' average logged self-reported per capita annual income in international dollars. Income is winsorized one-sided at the 99-percent level to account for misreported income. *Source: Gallup (2020).*

- **Wage Proxy**: Same as the variable *Income* but only includes individuals that work at least part-time according to the *Employed* variable. Individuals that are unemployed or out of workforce are coded as "NA". *Source: Gallup (2020).*

- **Extreme Poverty**: Binary variable equal to 1 if respondents' self-reported per capita annual income in international dollars is below the World Bank poverty line of 2.15 USD a day (785 USD per year). *Source: Gallup (2020).*

- **Perceived Income**: Index from 1 to 4 based on the respondent's satisfaction with their income measured with the following question "Which one of these phrases comes closest to your own feelings about your household income these days? "Living comfortably on present income"; "Getting by on present income"; "Finding it difficult on present income"; "Finding it very difficult on present income". *Source: Gallup (2020).*

- **Living Standard**: Binary variable equal to 1 if the respondent answers “Satisfied” to the following question “Are you satisfied or dissatisfied with your standard of living, all the things you can buy and do?” *Source: Gallup (2020).*

- **Community Basics**: Index variable taking values between 0 and 1. Based on the following seven questions: “In the city or area where you live, are you satisfied or dissatisfied with [sector]?”— “educational system or the schools,” “availability of quality healthcare,” “availability of good affordable housing,” “quality of water,” “quality of air,” “roads and highways,” and “public transportation systems.” It only includes observations of respondents answering to all questions and “Don’t know” and ”NA” answers are excluded. *Source: Gallup (2020).*

- **Corruption**: Binary variable equal to 1 if the respondent believes corruption is widespread within businesses in their country based on the question “Is corruption widespread within businesses located in this country, or not?” *Source: Gallup (2020).*

- **Migration** : Binary variable equal to 1 if the respondent believes their area is a good place for immigrants based on the question “Is the city or area where you live a good place or not a good place to live for immigrants from other countries?” *Source: Gallup (2020).*

- **Approval Own Government**: Binary variable equal to 1 if the individual approves of the job performance of the leadership of her own country based on the question “Do you approve or disapprove of the job performance of the leadership of this country? ” *Source: Gallup (2020).*

- **Democracy History**: Binary indicator equal to one if a country was majorly democratic in the 20 years before the sample period (1988-2007). *Source: Bjørnskov and Rode (2020).*

- **Technology Intensity**: Binary indicator equal to one if a country’s medium- and high-technology value added share in total manufacturing was above the mean value of the countries in the sample. Data is only available for 13 out of the 22 countries in the sample (South Africa, Morocco, Egypt, Mauritius, Senegal, Ghana, Zambia, Cameroon, Tanzania, Mozambique, Malawi, Rwanda and Ethiopia. *Source: UNIDO (2023).*

- **Leader Birth Region**: Binary variable that is set to one if at least one leader of country c was born in region r between 2007-2020. *Source: Bomprezzi et al. (2024).*

- **Chinese Leader Visit**: Binary indicator equal to one if a country received a visit by a Chinese president or premier between 2007-2020. *Source: Wang and Stone (2022).*

- **EU Trade Agreement**: Binary indicator equal to one if a country has a preferential trade agreement (Association Agreements or Economic Partnership Agreements) in place with the EU during the sample period. Source: `https://policy.trade.ec.europa.eu/eu-trade-relationships-country-and-region/negotiations-and-agreements_en`

- **Conflict**: Binary indicator equal to one if a ADM1 region experienced 5 or more conflict-related deaths during the sample period. We performed a point-to-polygon match if a conflict event could be assigned with certainty to an ADM1 region, i.e. when the geo-precision variable had a value smaller or equal 4. *Source: Sundberg and Melander (2013).*

- **Capital Region**: Binary indicator equal to 1 if an ADM1 region is the capital region of a country. In cases, where the capital region spanned over several ADM1 regions, I coded several ADM1 regions to 1.

- **China Strategic Partner**: Binary variable equal to one if a country is a strategic partner of China. *Source: Strüver (2017).*

- **Full-time Employed**: Binary variable equal to 1 if the respondents' employment status is one of the following: "Employed full time for an employer", "Employed full time for self". *Source: Gallup (2020).*

- **Self-Employed**: Binary variable equal to 1 if the respondents' employment status is "Employed full time for self". *Source: Gallup (2020).*

- **Employed**: Binary variable equal to 1 if the respondents' employment status is one of the following: "Employed full time for an employer", "Employed full time for self"; "Employed part time want full time" or "Employed part time do not want full time". *Source: Gallup (2020).*

- **Unemployed**: Binary variable equal to 1 if the respondents' employment status "Unemployed". *Source: Gallup (2020).*