The Impact of FinTech and Digital Transformation on Foreign Direct Investment and Bilateral Trade in Financial Services: The Case of the UK and India[1]

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Abstract:

The rapid digitisation of financial markets has significant implications for international trade and the global provision of financial services. This study examines the evolving role of FinTech and automation in reshaping global supply chains, focusing on the UK and India. While the UK leads in exports of financial services, India has established itself as a major player in ICT-related exports, bolstered by its growing FinTech capabilities. We explore how the increasing reliance on digital technologies, artificial intelligence, and internet-based financial services is altering the traditional dynamics of Foreign Direct Investment (FDI) and bilateral trade in financial services. Specifically, we assess whether FinTech-driven FDI complements or substitutes cross-border trade in financial services between these two economies. Our analysis is informed by empirical data on FDI flows, trade in services, and the FinTech ecosystem, utilising sectoral classifications from FDI Markets, OECD trade statistics, and Tracxn startup data. By applying econometric modelling and qualitative insights from industry interviews, we identify key factors driving FDI decisions in FinTech and assess their impact on trade patterns. Findings suggest that FinTech FDI is increasingly substituting traditional trade in financial services, particularly in the UK-India corridor. Regulatory barriers, market saturation, and an increasing preference for local market presence by financial service providers drive this shift. The study underscores the necessity for policymakers to consider the implications of digital transformation on trade policies and investment strategies, significantly as financial globalisation accelerates in the digital realm age.

Key words: FinTech; FDI; Trade in Services; FinTech ecosystem; State-space models

JEL codes: C22; C52; E22; F14; F65

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1. Introduction

The digital transformation of financial markets is reshaping international trade and the global organisation of financial services provision. Automation, digitalisation, and artificial intelligence (AI) are redefining traditional supply chains, reducing the dependence on low-cost labour and shifting the dynamics of globalisation (Altenburg et al., 2022). These changes have profound implications for financial technology (FinTech), where internet connectivity, speed, and mobile accessibility play a crucial role in market expansion and service delivery. This study examines the evolving landscape of FinTech-driven trade and foreign direct investment (FDI) through a comparative analysis of the United Kingdom (UK) and India—two economies with distinct but complementary strengths. The UK, a global leader in financial services, derives 35% of its sectoral exports from financial services, while India has emerged as a dominant force in ICT-related exports. As the nearshoring of financial services and technology gains traction, FDI is increasingly substituting traditional cross-border trade. This paper explores how these trends influence job creation, trade in financial services, and the underlying FinTech ecosystem, ultimately shaping bilateral FDI patterns between the UK and India.

2. FDI and Trade in Services

The evolution of foreign direct investment (FDI) and bilateral trade in FinTech and financial services is taking place within the broader transformation of financial services driven by the global FinTech revolution (Markose et. al, 2025). FDI has long served as a key mechanism for financial sector expansion, traditionally utilised by multinational banks to enter developing and emerging markets (Moshirian, 2001). However, this trend is no longer restricted to legacy financial institutions. FinTech startups, ICT companies, and other financial service providers are increasingly employing FDI to establish operations in new markets (Amendolagine et al., 2013).

This financial transformation is also altering the composition of trade in financial services, with its share in overall trade volumes increasing. Several factors contribute to this shift, including the rise of internet-driven financial services, blockchain technology, and digital currencies. Investment in digital infrastructure and connectivity across developed and developing economies is enabling greater bilateral and multilateral trade in financial services (Clavijo & Pantaleon, 2020). At the same time, FDI plays a crucial role in transferring new technologies and innovations to these markets, further shaping the financial services landscape (Clavijo & Pantaleon, 2020, Markose et. al , 2025).

One of the notable consequences of the FinTech revolution is the diversification of ownership structures among multinational banks, financial service startups, and small and medium enterprises (SMEs) worldwide (Clavijo & Pantaleon, 2020). While increased FDI in financial services is a relatively recent phenomenon, literature has long established FDI as a key driver of globalization in the sector. FDI brings capital, expertise, and technology to host-country financial markets, fostering competition, innovation, and diversification. The Committee on the Global Financial System (2004) found that financial services FDI plays a pivotal role in integrating emerging economies into the global financial system, with regulatory improvements being an essential factor in facilitating this process.

Jithin and Suresh (2020) provide further empirical support for the relationship between FDI and financial development, arguing for a two-way effect: well-developed financial markets attract greater FDI, and in turn, foreign capital flows contribute to further financial development. This relationship is evident in both developed economies like the European Union and emerging economies such as India. Overall, existing literature highlights the dynamic nature of financial services, the influence of FDI in globalizing the sector, the evolving composition of trade, and the critical role of technology in driving these transformations. Regulatory and institutional frameworks remain key determinants in managing the impacts of financial globalization.

2.1 Substitution vs. Complementarity in FinTech FDI and Trade in Financial Services

A crucial aspect of the interaction between trade in financial services and FinTech foreign direct investment (FDI) is the extent to which FDI substitutes for or complements cross-border trade. Empirical research has documented both substitution and complementary relationships between bilateral trade and FDI across various industries, including financial services. The debate over whether FDI replaces or enhances trade in services is particularly relevant to FinTech and financial services, necessitating a focused analysis of industry-specific data. This study aims to determine whether the relationship between FinTech FDI and trade in financial services is primarily substitutional, particularly within the UK-India context.

A key driver of increasing FDI flows is the necessity to finance the digital transformation of economies. In 2023, significant capital flows targeted areas such as Payments, InsurTech, Cybersecurity, WealthTech, and Blockchain & Cryptocurrency (KPMG, 2024). However, the relationship between FDI and bilateral trade in financial services is affected by multiple factors, making it challenging to categorise them strictly as substitutes or complements. The nature of financial services, policy environments, and market structures play significant roles in determining their effective interaction.

FDI can complement trade in financial services by enhancing the financial infrastructure of host countries. Foreign financial institutions that invest in local banking and financial sectors can facilitate an increase in cross-border trade in these services. Furthermore, FDI provides firms with a local presence, enabling them to tailor their financial products to meet local market needs, which can strengthen trade relationships. Studies have confirmed this complementary relationship in various contexts: Zarotiadis and Mylonidis (2005) found this effect in the British economy across multiple industries. Research on German banks (Buch & Lipponer, 2004) also identified complementarity, with geographical and cultural factors influencing the degree of international banking expansion. Martinez-San Roman et al. (2012) confirmed that FDI and trade complement each other in the financial markets of the European Union.

However, this complementarity depends on the absence of regulatory restrictions and previous analysis suggests that it develops alongside regulatory alignment and economic and financial integration. In the present analysis we deal with considerable regulatory obstacles, particularly in the case of India, especially for trade in digital services. The OECD (2022) Digital Services Trade Restrictiveness Index, shows UK has a low DSTRI of 0.06, indicating low barriers, while India has the highest DSTRI of .36 of all countries surveyed. For example, India imposes stringent licensing requirements on foreign financial service providers, creating barriers for foreign firms that lack the necessary approvals. While the UK maintains low barriers to service trade, India's higher non-tariff barriers indicate that complementarity may not apply in this instance. Empirical studies show that in markets with significant regulatory restrictions, FDI often replaces cross-border trade as firms seek alternative means of entry.

In some scenarios, FDI can substitute for trade in financial services. When foreign firms establish local operations via FDI, they may compete directly with domestic firms, reducing the need for cross-border trade. This substitution effect is particularly evident in saturated markets, such as the UK’s financial services sector. In cases where regulatory barriers hinder trade, FDI becomes a preferred strategy for market entry. This pattern is observable in India, where foreign financial firms often opt for FDI over trade due to high market entry restrictions.

Chang and Gayle (2009) argue that the relationship between FDI and trade is influenced by variables such as foreign exchange (FOREX) volatility, which can drive firms to favour FDI over trade in uncertain financial conditions. The nature of financial services also plays a role—banking and insurance sectors often experience complementarity, while services like portfolio management may be more easily substituted by FDI, given the ability to operate remotely.

The UK-India financial relationship provides strong indications of a substitutional trend. Interviews with Indian financial service firms, such as I-Exceed, reveal that FDI is increasingly replacing cross-border trade as firms establish ground presence in each economy. The primary motivations include growing interdependencies in financial services, an expanding economic relationship between the two countries, and the necessity of local presence to meet regulatory and operational requirements. The rapid expansion of the FinTech sector—driven by consumer demand and technological advancements—has further incentivised firms to favour FDI over trade.

The relationship between FDI and bilateral trade in financial services is highly context-dependent, influenced by regulatory environments, market saturation, and the nature of the financial services provided. While the literature broadly suggests a complementary relationship, empirical evidence from the UK-India financial services sector indicates a stronger tendency towards substitution. The increasing preference for FDI over trade in services aligns with India's regulatory landscape and the evolving structure of financial globalisation. Future research and industry data analysis will be critical in confirming the extent and sustainability of this substitution effect.

3.Data and Methods

3.1 FDI Data Collection and Classification

FDI data for fintech-related sectors and services is sourced from FDI Markets. The dataset spans the period from its inception in 2003 to March 2023 and includes monthly records of FDI projects. Each project provides details about the investing company, source country, and destination country. Since there is no dedicated category for fintech FDI within this database, a classification methodology is employed to sort relevant projects. FDI projects are first categorised under 'sectors', then further classified into 'clusters' and 'activities' to filter those related to financial technology.

To distinguish the relevance of different FDI projects to fintech, we apply a two-tier classification. Tier 1 consists of projects categorised directly under the 'Financial Services' sector and projects from the 'Business Services' or 'Software & IT Services' sectors that explicitly relate to financial services. These are primarily investments made by banks and non-bank financial institutions. Tier 2 includes projects where the investing entities are technology firms that contribute to the financial ICT infrastructure. These projects involve Data Solutions, IT-related back-office operations, and customer service centres. Over time, Big Tech firms have become increasingly significant players in financial services, particularly in the India-to-UK FDI flows. This trend supports the broader literature indicating that technology companies are entering the financial sector. While Tier 1 projects are directly fintech-related, Tier 2 projects contribute indirectly to fintech. Given the lack of a universally accepted definition of fintech, distinguishing fintech elements within Tier 2 projects requires further examination.

For this study, we adopt the broader Tier 2 definition to ensure comprehensive coverage of all fintech-related FDI activity. This approach is beneficial, as it provides a larger dataset, which is particularly useful for empirical analysis. It does however introduce a degree of subjectivity in assessing indirectly the significance of individual FDI projects to the fintech sector. We have tried to reduce this subjectivity by concurrent independent classification by two researchers , followed by an internal resolution of projects that were initially classified under different type in order to ensure a consensus classification.

3.2 Data Aggregation and Key FDI Measures

To facilitate the analysis, the data on individual FDI projects are aggregated on monthly basis. The total capital investments and jobs created are summed for each month (across all projects), creating a continuous time series for bilateral FDI between India and the UK. These two variables are the primary focus of our econometric analysis, serving as key indicators of fintech-driven FDI. The dependent variables in the specification further below are ether jobs creates 9in thousands) or capital invested (in USD millions) on a monthly basis

Trade data on financial services is extracted from the OECD Statistics Database. The dataset focuses on three fintech-relevant industry sectors: Financial Services, Insurance & Pension Services, and Telecommunications, Computer, and Information Services. Since the OECD database provides trade data in multiple formats, we use the Final Balanced Value, which reconciles discrepancies between national trade authorities. Given the rising FDI in fintech-related services, we expect a substitution effect, where increased FDI displaces cross-border trade in these financial services. All financial flows are measured in USD millions.

To assess the significance of financial and ICT services in each country’s trade, we extract data from the World Bank Trade Statistics Database. This includes the share of financial and insurance services in total exports and imports for both the UK and India, as well as the share of ICT services in total services trade. These measures provide insights into the relative importance of financial services in each country's overall trade structure. They also serve as indirect indicators of sectoral development and competitiveness, helping to contextualise fintech's role in bilateral investment.

To capture the strength and dynamism of the fintech sector, we construct two key measures using data from Tracxn: (1) Ecosystem Size – the number of new fintech startups per month. This metric reflects the quality of the fintech ecosystem, as a well-developed sector should attract more startups; and (2) Ecosystem Funding – the total capital raised in monthly funding rounds by fintech companies. This measure tracks investment activity but does not distinguish between funding stages (e.g., seed versus growth-stage investment). Ecosystem si

To address potential lag effects, we also compute 1-year and 2-year running averages of these measures. If the longer-term averages exhibit greater explanatory power in our models, it would suggest that the impact of ecosystem development is sustained over time. We also construct a Digital Connectedness Index using Confirmatory Factor Analysis. This index comprises fixed-line subscriptions per 1,000 inhabitants, mobile subscriptions per 1,000 inhabitants, international bandwidth usage, and internet users per 1,000 inhabitants. While this measure was considered in our analysis, it did not feature prominently in the final results, so we do not emphasise it further.

One challenge in the analysis is that different datasets have varying time frequencies. The FDI and fintech ecosystem data are monthly, while the trade and financial sector measures are reported annually. To align these datasets, we apply polynomial interpolation to convert annual data into monthly estimates. This ensures consistency while preserving logical accuracy. The interpolation is handled as follows: (1) Stock variables (e.g., digital connectedness) are interpolated from their recorded measurement dates. (2) Flow variables (e.g., trade data) utilise a trailing-year approach. For instance, the March 2019 data point represents trade activity from April 2018 to March 2019.

This approach allows us to maximise data points while maintaining consistency for time-series analysis. By integrating different datasets, our study provides a rigorous empirical investigation into the evolving role of fintech-driven FDI, the substitution effect on trade, and the broader implications for financial globalisation.

3.3 Model specification:

The general model specification is that of a local linear trend model with (possibly time varying) regression effects as described below:

$$Y_t = \mu_t + \sum \beta_{it} X_{it} + \epsilon_t$$

$$\mu_{t+1} = \mu_t + \delta_t + \eta_{\mu,t}$$

$$\delta_{t+1} = \delta_t + \eta_{\delta,t}$$

$$\beta_{i,t+1} = \beta_{it} + \zeta_{i,t}$$

$$\eta_{\mu,t} \sim N\left(0, \sigma_{\mu,t}^2\right), \eta_{\delta,t} \sim N\left(0, \sigma_{\delta,t}^2\right), \zeta_{it} \sim (0, \sigma_i^2)\ for\ \forall i$$

In this specification the FDI measure (capital or jobs) consists of a local linear level μ_t which incorporates a local trend δ_t and a set of regression effects $\beta_{it} X_{it}$. Whenever the corresponding variance terms associated with the regression effects σ_i^2 are zero, these reduce to fixed regression effects, similar to those in classical regression models. Otherwise they are time evolving effects.

The primary approach to estimating such time-varying parameter models relies on their state-space representation. For state-space models, the Kalman filter, which facilitates one-step-ahead conditional expectations for the time-varying parameters, can be utilised to construct the likelihood function (by representing all parameters and, consequently, their contributions to the likelihood as a function of the initial parameters). The latter can then be either directly optimised (as in the frequentist framework) or employed to obtain a posterior (in Bayesian approaches). Subsequently, the Kalman smoother can be applied to the estimated parameters to incorporate the full sample information (since the filtered estimates only account for information from previous time periods). Here, we rely on Bayesian estimation via Markov Chain Monte Carlo (MCMC).

In order to select a more parsimonious model, we need to therefore do two distinct selection tasks. We apply these with regard to all model parameters, but it is easier to explain these in relation to the regression effects. First, we need to select which parameters evolve over time and which are time invariant. Whenever the corresponding variance terms associated with the regression effects σ_i^2 are zero, these reduce to fixed regression effects, similar to those in classical regression models. Otherwise, they are time-evolving effects. Second, we need to establish which regression coefficients (i.e. β_i) are zero. Whenever they are zero, the corresponding regression effect will be excluded from the model. In simple terms, we conduct simultaneous variance and variable selection. To achieve this, we utilise Bayesian shrinkage.

There are two main approaches to sparsity in Bayesian statistics: discrete mixtures that place a point mass at zero and continuous prior which places large density at zero. ones. The former approach is the so-called spike-and-slab prior (e.g., Beauchamp 1988; George and McCulloch 1993), along with the stochastic search variable selection (SSVS) priors (George and McCulloch, 1993). The latter approach can be exemplified by, for instance, the Bayesian Lasso prior (Park and Casella, 2008), the normal–gamma prior (Griffin and Brown, 2011), and the horseshoe prior (Carvalho et al., 2010).

Frühwirth-Schnatter and Wagner (2010) reformulated the variance selection problem for state space models as a variable selection issue in the so-called non-centred parameterisation of the state space model. This enables one to shrink both variances and fixed parameters simultaneously within the same specification. More specifically, Frühwirth-Schnatter and Wagner (2010) employed spike-and-slab priors; however, the general principle is applicable to other shrinkage priors. Belmonte et al. (2014) utilised the Bayesian Lasso prior for variance selection in time-varying parameter models, while Bitto and Frühwirth-Schnatter (2015) applied the Normal-Gamma (NG) prior of Griffin and Brown (2011).

The results reported here are derived from Bayesian lasso (Park and Casella, 2008), one of the most popular shrinkage approaches. However, we have also tried several alternative shrinkage methods, namely the horseshoe (HS) prior of Carvalho et al. (2010), the Normal-Gamma (NG) prior of Griffin and Brown (2010), the Dirichlet-Laplace (DL) prior of Bhattacharya et al. (2015), the Normal-mixture of Inverse Gamma (NMIG) prior of Ishwaran and Rao (2005), the stochastic search variable selection (SSVS) prior of George and McCulloch (1993, 1997), as well as the triple gamma prior of Cadonna et al. (2020). The final results from these alternative specifications (after sparsification) are not qualitatively different. Therefore the interpretation of the results provided hereafter would not change if alternative estimation method was applied.

The issue with Bayesian shrinkage estimation is that, unlike the frequentist approach, it does not produce parameters that are exactly zero. This means that shrinkage priors must be combined with some form of hard thresholding to induce sparsity in the model structure (i.e., to impose zero restrictions). Applying an ad hoc approach to this could, however, be detrimental to the model results.

However, Ray and Bhattacharya (2018) proposed a computationally simple algorithm, namely the signal adaptive variable selector (SAVS), for introducing sparsity in shrinkage estimates.

SAVS can be trivially applied to the results from an already estimated model. Alternatively, as suggested by Huber et al. (2021), the SAVS algorithm can be applied at each step of the MCMC estimation. This can be implemented during estimation or, alternatively, can be done post-estimation over the MCMC draws. Applying SAVS over the MCMC draws allows one to incorporate and account for the uncertainty pertaining to estimation. Our limited experience also seems to suggest that, compared to post-estimation applications, it results in a more stable results structure. Indeed, as we have noted above, a range of alternative priors results in qualitatively similar outcomes, which is not the case in the post-estimation application (i.e. if the alternative priors are applied and only then SAVS is carried out over their results). Furthermore, we apply the SAVS steps during estimation. The advantage of this is that we obtain sparsified parameter chains to which the standard convergence diagnostics can be applied. Applying SAVS over the already completed MCMC draws can also be used instead, but it appears that it can be unstable for spike and slab and SSVS priors, probably due to computational challenges.

4. Results

We estimate three separate model specifications for each country. The first two explain the jobs and capital attributed to FDI. The last one is similar to the jobs model, but also includes in the pool of explanatory variables the capital invested (in FDI). If the algorithm removes the capital invested as an explanatory variable, the last model will coincide with the second one. However, for both countries, this was not the case.

The final models have the following form:

$$Y_t = \mu_t + \sum \beta_i X_{it} + \epsilon_t$$

$$\mu_{t+1} = \mu_t + \delta_t + \eta_{\mu,t}$$

$$\delta_{t+1} = \delta_t + \eta_{\delta,t}$$

$$\eta_{\mu,t} \sim N\left(0, \sigma^2_{\mu,t}\right), \eta_{\delta,t} \sim N\left(0, \sigma^2_{\delta,t}\right)$$

The first important result is that all regression effects in all the six models ($i.e.\ \beta_i$) are reduced to fixed (i.e. not varying in time) coefficients. These fixed coefficients are in fact standard regression effects and can be interpreted accordingly. All models include local linear trend stochastic components (i.e. δ_{t+1}). This uniformity of the obtained results facilitates their presentation. The regression effects for the UK are presented in Table 1 below.

Table 1. Regression Effects   for FDI into the UK

	UK capital		UK jobs		UK jobs	
	Coef	SE	Coef	SE	Coef	SE
Capital investment					0.190	0.047
FinS imports	-0.030	0.013	-0.192	0.048		
IPS imports	-0.047	0.023	-0.210	0.061	-0.355	0.063
InsFS Import share	1.513	0.351	5.710	0.992	5.740	0.697
Size of FinTech	54.064	23.677	12.955	4.269	15.470	5.923
FinTech Funding 2yrs	92.513	1.138	54.064	7.289	15.649	6.783

All models consistently retain the same regression effects. Since capital investment is only allowed (by design) to enter the last model, the only structural difference between the regression parts of the three UK models is the exclusion of financial services imports (from India into the UK). We briefly comment on these regression effects below.

The financial services bilateral imports (FinS imports i.e. Indian exports of financial services into the UK) show a significant negative effect on both FDI capital and jobs. This confirms the expected substitution effect between FinTech FDI and trade in services. We also observe a similar substitution effect concerning Insurance and Pension services (IPS imports), which is consistent across all three model specifications.

It is worth noting at this point that the last model presents a notably different interpretation. As it already includes capital investment as a job-creation factor, the remaining regression effects should be viewed as modifiers to this primary (capital-induced) effect. In other words, they need to be interpreted as modifiers of the capacity for job creation, rather than job creation itself, as seen in the second model. Therefore, while reducing imports of insurance and pension services from India into the UK limits the job creation capacity of Indian FinTech FDI investments, the corresponding trade flows of financial services do not. This indicates that displacing trade in insurance and pension services generates additional FinTech jobs via FDI, but financial services reallocation (from trade to FDI) only influences the absolute level of FinTech jobs (as in model 2).

The relative share of insurance and financial services in the UK total services trade (InsFS Import share) is positively related to all three FDI measures: the significance of insurance and financial services in the total UK services imports affects (positively) FDI in terms of both capital, jobs and job creation capacity. Since this particular variable is retained across all model specifications (for all three specifications for both countries), one can assume that it is a universal measure of probably the pull of the corresponding domestic market. In other words when the insurance and financial services sector increases its relative importance it pulls in FinTech FDI. In other words, this variable probably serves as a proxy for the relative domestic demand for such services.

The last two retained regression effects measure the quality of the FinTech ecosystem and as such they do have the expected positive effect. Two things are however noteworthy in considering the ecosystem effects. The first is that out of the three measures of funding, the one that was retained is that of average (monthly) funding over the preceding two years (rather that the average funding over the last year or the current funding raised). This suggests that the corresponding 'funding' effects are longer term in that they last over longer time periods. Since the funding raised cannot be considered as a direct 'cause' for FDI, but it is rather an indirect measure of the quality of the FinTech ecosystem, such longer term average, suggesting that the UK FinTech ecosystem is characterised by a significant 'depth'. However since we have only included three measures for raised funding and the estimation have selected the boundary one (the one with longest term amongst the considered measures), it is unclear about the exact depth of the funding infrastructure (which could have been the case if e.g. we have included longer terms averages and the selected one was not a boundary one).

What is also interesting is that the ecosystem measures also affect the job creation capacity of FDI investments positively. There were no prior expectations for such effects And yet such a result is nevertheless quite significant. One could expect that at initial stages of any industry growth to be characterised with greater job creation ability which however might decline and even reverse as it reaches maturity. So, this result might signify that the fintech industry has some way to go before reaching a mature stage in its development.

Table 2 present the corresponding regression effects for the three Indian specifications.

Table 2. Regression Effects for FDI into India

	India capital		India Jobs		India Jobs	
	Coef	SE	Coef	SE	Coef	SE
Capital investment					5.273	0.971
FinS imports	-0.268	0.034	-1.274	0.496	-0.127	0.048
ICT imports	-0.273	0.143	-0.060	0.019		
InsFS Import share					103.581	8.392
Size of FinTech	0.010	0.004	0.008	0.002	0.673	0.093
FinTech Funding	0.009	0.002	0.074	0.028		
Fintech Funding 1 yr					72.151	6.098

The first point to make when considering the above results is that similarly to the case of the UK, the first two specification are identical with regard to the regression effects they retain

Again, the results confirm the trade-in-services substitution effect via the negative effect of the UK-India financial services trade flows (which are India's imports of financial services from the UK). In contrast to the UK case, the financial services flows also affect the job-creation capacity of FinTech FDI. In other words, the substitution of financial services trade by FinTech FDI creates additional jobs.

We also observe a similar substitution effect for ICT trade, but not concerning job creation capacity. However, it seems somewhat odd that we find a positive effect from ICT imports rather than from ICT exports. Thus, while not illogical, this result warrants further investigation. Given that India is a major exporter of ICT services, it is necessary to take a closer look at the types of ICT services the UK could be exporting to India. One possible explanation might be the provision of compliance and certification expertise, which could be classified as ICT.

The significance of insurance and financial services in India's overall services imports has a positive effect on the job-creation capacity of FinTech FDI. However, unlike the UK, it is omitted from the capital and (absolute) jobs models. The latter could be due to regulatory constraints that prevent direct trade effects.

Finally, the ecosystem measures indicate significant and positive effects across all models. However, while the first two models utilise the contemporary measure of increased funding, the job creation capacity specification maintains the one-year averaged measure. This suggests that India's FinTech ecosystem could benefit from a greater depth of funding arrangements, particularly as such depth is highly conducive to job creation capabilities.

Another observation relates to the jobs-creating effect of FinTech FDI capital invested, which is considerably higher in India than in the UK. This could have several explanations, including earlier stages of FinTech sector growth, lower relative labour costs, higher compliance costs (India has higher barriers to trade in services), etc.

In addition to the regression effects, all the above models also include a local linear trend. Such a component may have a complex justification. Fortunately, in this particular case, as the remainder of the corresponding models consists solely of fixed regression effects—which have a straightforward explanation as a combination of services trade substitution and the pulling power of the FinTech ecosystem—the explanation for the local linear trend becomes somewhat simplified. It can essentially be viewed as reflecting all determinants and underlying processes that were (unintentionally) omitted by the specification of regression effects.

Let us first consider the local linear trend for the UK FDI. These are shown on figures 1-3.

Figure 1 FinTech FDI capital investments in the UK

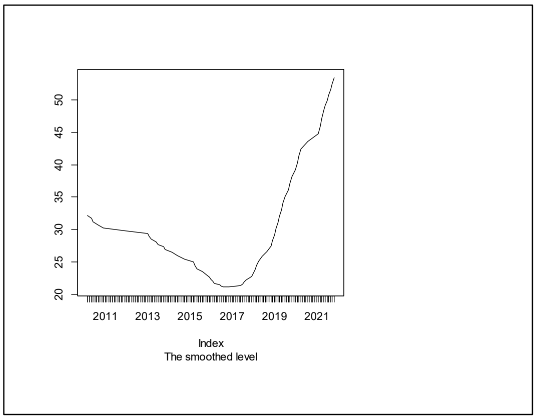


Figure 2 FinTech FDI jobs in the UK

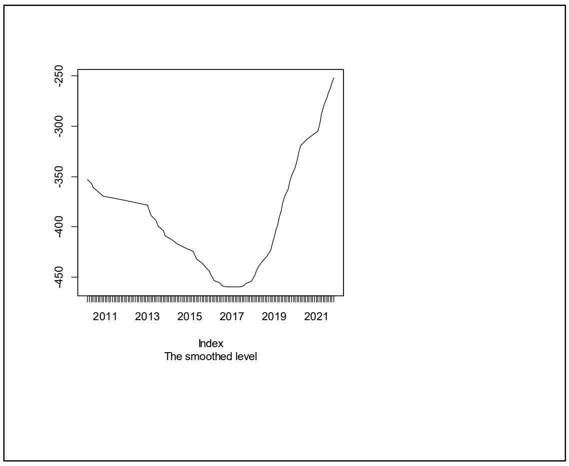
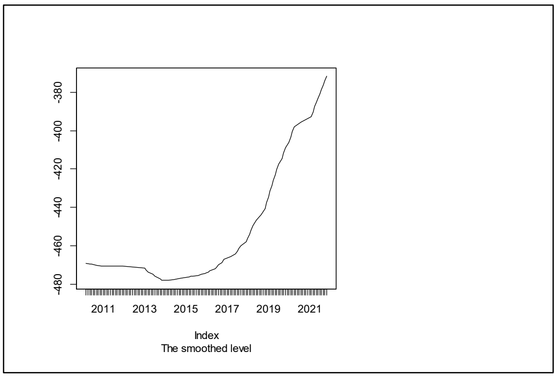


Figure 3. Local level of job creation capacity of fintech FDI



The local linear trends for capital FDI investments (figure 1) and jobs created (figure 2) look very similar. They both show a moderate downward trend up to 2017, followed by a dramatic upward movement afterward. This shows that a structural change in the FinTech FDI relationship in 2017 pulled considerable FDI into the UKL beyond the trade substitution ecosystem effects we have discussed above.

Regarding the additional job creation capacity of FDI (i.e. the last model specification; see figure 3), we observe a similar structural change. However, this change occurs earlier, and the initial period is characterised by an almost constant job creation capacity effect as opposed to the downward trend in the other two models. This indicates that, over time, the unit of capital invested in FDI in the UK reduces the average number of jobs created. This could suggest that fintech has become more productive and thus requires less labour per unit of capital. Such results imply that job creation capacity might serve as a leading indicator in FDI investigations.

It is noteworthy that the India regression effects demonstrated that job creation capacity is influenced by longer-term trends, particularly in funding infrastructure.

Figure 4 FinTech FDI capital invested in India

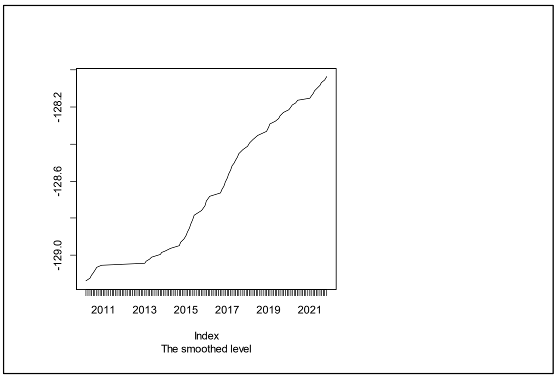


Figure 5 FinTech FDI jobs in India

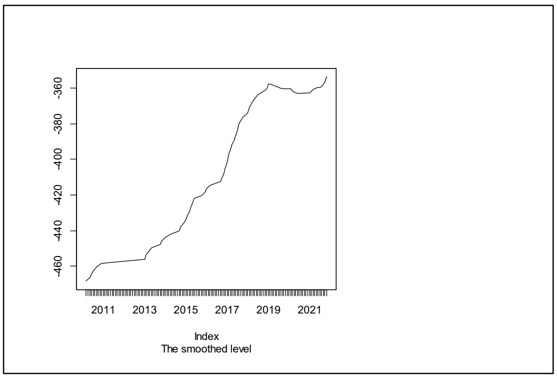
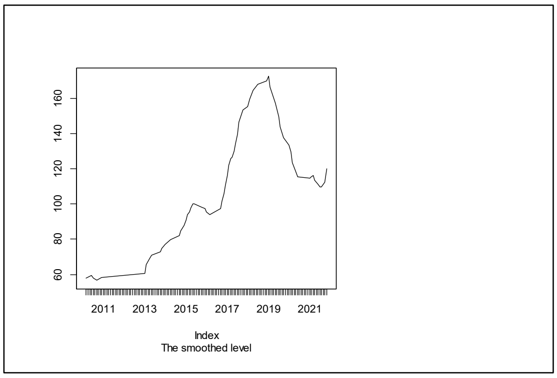


Figure 6 FinTech FDI job creation capacity in India



A somewhat related picture emerges regarding India (see Figures 4-5). Once again, we observe a structural change, which took place around 2013. However, around 2019, the job creation capacity effect reduced, flattening the job creation effect. The latter could be a COVID-related effect, and there are some early indications that this has been subsequently reversed.

5. Conclusions

This study provides a comprehensive analysis of FinTech-related bilateral FDI between the UK and India, revealing key structural shifts and unique driving forces that differentiate this relationship from traditional FDI and trade patterns. The substitution effect between FDI and bilateral trade in financial services stands as a defining feature, though its underlying causes differ significantly between the two economies.

For India-to-UK FDI, this substitution effect is driven by a strategic realignment in cross-border service provision, shifting from offshoring to nearshoring and onshoring. As digital transformation diminishes the relevance of location, firms increasingly opt to establish a direct presence through FDI rather than relying on conventional trade mechanisms. In contrast, UK-to-India FDI is largely shaped by regulatory barriers to trade in services, compelling UK firms to navigate these constraints by investing directly in Indian operations. This divergence highlights the dual nature of FinTech FDI - one rooted in operational efficiency and evolving business models, the other in regulatory adaptation and market access strategies.

Beyond substitution effects, our findings underscore the powerful pull of domestic market conditions and the quality of each country's FinTech ecosystem in shaping FDI flows. The strength of financial services in a country's overall trade portfolio acts as a magnet for investment, while the robustness of its FinTech startup ecosystem—as measured by startup activity and funding levels—plays a critical role in attracting foreign capital.

A striking distinction emerges when examining the time horizon of ecosystem effects. In the UK, FinTech FDI is more responsive to long-term trends, indicating that early-stage funding flows influence investment decisions only after a significant time lag. This suggests a more stable regulatory and investment climate, wherein long-term planning and market maturity allow investors to take a broader strategic approach. Conversely, India's FinTech FDI dynamics are more closely aligned with short-term variations in funding flows, reflecting greater sensitivity to regulatory shifts, policy changes, and market volatility. This shorter-term alignment signals an investment environment in transition, where adaptability to changing regulations and rapid market developments is crucial.

Finally, a structural shift in FinTech FDI flows is evident, with a notable acceleration around 2016 in the UK and a slightly earlier surge in India, around 2013. This aligns with key milestones in global FinTech expansion, regulatory changes, and digital transformation trends, reinforcing the notion that FinTech investment patterns are shaped not only by bilateral factors but also by broader global market forces.

In conclusion, the UK-India FinTech FDI relationship represents a critical case study of how technology, regulation, and market structure interact to reshape cross-border financial services investment. As FinTech continues to disrupt traditional financial markets, understanding these nuanced investment flows is essential for policymakers, industry leaders, and investors navigating this new era of financial globalisation. The evolving nature of FinTech FDI suggests that future research and policy frameworks must remain adaptive, as the interplay between regulatory environments, ecosystem maturity, and strategic business shifts will continue to redefine the future of cross-border financial services investment.

References:

Altenburg, T., N. Corrocher and F. Malerba (2022) China's leapfrogging in electromobility. A story of green transformation driving catch-up and competitive advantage, *Technological Forecasting and Social Change*, 183.

Amendolagine, V., A Boly, N.D. Coniglio, F. Prota and A Seric (2013) FDI and Local Linkages in Developing Countries: Evidence from Sub-Saharan Africa, *World Development*, 50, 41-56.

Belmonte M, Koop G and Korobilis D (2014) Hierarchical shrinkage in time-varying coefficient models. *Journal of Forecasting* 33(1), 80–94

Bhattacharya A, Pati D, Pillai NS and Dunson DB (2015) Dirichlet–Laplace priors for optimal shrinkage. *Journal of the American Statistical Association* 110(512), 1479–1490

Bitto A and Fruhwirth-Schnatter S (2019) Achieving shrinkage in a time-varying parameter model framework. *Journal of Econometrics* 210(1), 75–97

Buch, C M. and A Lipponer(2004) FDI Versus Cross-Border Financial Services: The Globalisation of German Banks (2004). Bundesbank Series 1 Discussion Paper No. 2004,05, http://dx.doi.org/10.2139/ssrn.2785050

Cadonna, A, S Frühwirth-Schnatter and P Knaus. (2020) Triple the Gamma—A Unifying Shrinkage Prior for Variance and Variable Selection in Sparse State Space and TVP Models, *Econometrics* 8, no. 2: 20. https://doi.org/10.3390/econometrics8020020

Carvalho CM, Polson NG and Scott JG (2010) The horseshoe estimator for sparse signals. *Biometrika* 97(2), 465–480.

Chang Y.-M. & P Gayle, (2009). Exports versus FDI: do firms use FDI as a mechanism to smooth demand volatility?, *Review of World Economics*, 145(3), 447-467.

Clavijo, Y. T., & Pantaleón, H. (2020). Foreign Direct Investments into FinTech and Blockchain Technology Startups in Latin America. *The University of Miami Inter-American Law Review*, *51*(1), 53–83.

Committee of the Global Financial System (2004) Foreign direct investment in the financial sector of emerging market economies, CGFS Papers No 22, Bank of International Settlements, available at: https://www.bis.org/publ/cgfs22.pdf

George EI and McCulloch RE (1993) Variable selection via Gibbs sampling. *Journal of the American Statistical Association* 88(423), 881–889

George EI and McCulloch RE (1997) Approaches for Bayesian variable selection. *Statistica Sinica*, 339–373

George EI, Sun D and Ni S (2008) Bayesian stochastic search for VAR model restrictions. *Journal of Econometrics* 142(1), 553–580

Goldberg, L. S. (2004). Financial-sector FDI and host countries: New and old lessons.

Griffin, J E. and P J. Brown. (2011) Bayesian hyper-lassos with non-convex penalization. *Australian & New Zealand Journal of Statistics* 53: 423–442.

Huber, F., G. Koop and L. Onorante (2021) Inducing Sparsity and Shrinkage in Time-Varying Parameter Models, *Journal of Business & Economic Statistics*, 39:3, 669-683

Ishwaran H and J. S. Rao.(2005) Spike and slab variable selection: Frequentist and Bayesian strategies. *Annals of Statistics*, . 33 (2) 730 – 773.

Jithin, P and B M Suresh (2020) Testing for the effectiveness of inflation targeting in India: A Factor Augmented Vector Autoregression (FAVAR) approach, *Journal of Central Banking Theory and Practice*, 9 (3), 163-182.

Kastner G and Fruhwirth-Schnatter S (2014) Ancillarity-sufficiency interweaving strategy (ASIS) for boosting MCMC estimation of stochastic volatility models. *Computational Statistics & Data Analysis* 76, 408–423

KPMG (2024) Pulse of FinTech H2'23: Global analysis of FinTech funding, available online at: https://assets.kpmg.com/content/dam/kpmg/xx/pdf/2024/02/pulse-of-fintech-h2-2023.pdf

Markose, S. M. and Khan, A. and Kostov, P. and Arun, T. and Murinde, V., FinTech Ecosystem Impact on FinTech Startup Performance: Perspectives from UK & India (February 28, 2025). Available at SSRN: https://ssrn.com/abstract=

Martinez-San Roman, V. M Bengoa-Calvo and B. S. Robles (2012) Foreign Direct Investment and Trade: Complements or Substitutes? Empirical Evidence for the European Union, *Technology and Investment* 3(2):105-112.

Moshirian, F. (2001) Financial systems in the new millennium, *Journal of Multinational Financial Management*, 11(4–5),315-320.

Moshirian, F. (2001). International investment in financial services. *Journal of banking & Finance*, 25(2), 317-337.

OECD (2022) Digital Services Trade Restrictiveness Index, available at https://qdd.oecd.org/subject.aspx?Subject=STRI_DIGITAL

Zarotiadis, G and N Mylonidis (2005) FDI and Trade in the UK: Substitutes or Complements?, ETSG Conference, Dublin.