Journal of Monetary Economics xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of Monetary Economics

journal homepage: www.elsevier.com/locate/jmoneco

Cross country stock market comovement: A macro perspective☆

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A R T I C L E I N F O

Article history:
Received 8 April 2021
Revised 11 May 2022
Accepted 16 May 2022
Available online xxx

JEL classification:
G15
F21
F23
G12
F44

Keywords:
Stock market comovement
Foreign direct investment
Multinational firms
Asset pricing
International trade
Portfolio diversification

A B S T R A C T

Since the 1990s, there has been a simultaneous rise in cross-country stock market correlations and FDI positions. We establish an empirical relationship between these two, for pairs of developed economies that survives controlling for relevant factors. At firm level, we find that stock returns of multinationals that invest in technology capital are more correlated with world stock markets. Using a calibrated two-country asset pricing model with multinationals, we find that the increase in FDI accounts for one third of the rise in the observed stock market correlations. When allowing for increases in trade and portfolio diversification, we find that these two factors do not generate an increase in stock market correlations.

☆ We thank the *British Academy* for generously funding this project via the Newton Advanced Fellowship scheme (2017–2022), and the *Cambridge Endowment for Research in Finance (CERF)* for financial support. We are grateful to internal seminar participants at the Department of Economics of Stony Brook University and the Faculty of Economics at the University of Cambridge. Also, we thank Marina Azzimonti, Harjoat Bhamra, Charlie Brendon, Vasco Carvalho, Tiago Cavalcanti, Fabrice Collard, Martial Dupaigne, Julian di Giovanni, Amit Goyal, Giammario Impulliti, Gabriel Mihalache, Kamiar Mohaddes, Rafael Rogo and Argyris Tsiaras for fruitful discussions and suggestions for this project. Thanks go to seminar and conference participants at EEA 2019, MMF 2019, Cambridge-Lausanne Finance Workshop, Midwest Macro Meetings 2019, European Winter Meetings of the Econometric Society 2020, Toulouse School of Economics and Bank of Greece. Finally we thank an anonymous referee and our editor Carolin Pflueger for their valuable suggestions to improve the paper. The authors acknowledge access to the Bureau van Dijk Orbis data base via Sabanci University, where Orhan Erem Atesagaoglu is a visiting lecturer. An earlier version of the paper was circulated under the title '*Foreign Direct Investment as a Determinant of Cross-Country Stock Market Comovement*'.

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https://doi.org/10.1016/j.jmoneco.2022.05.005

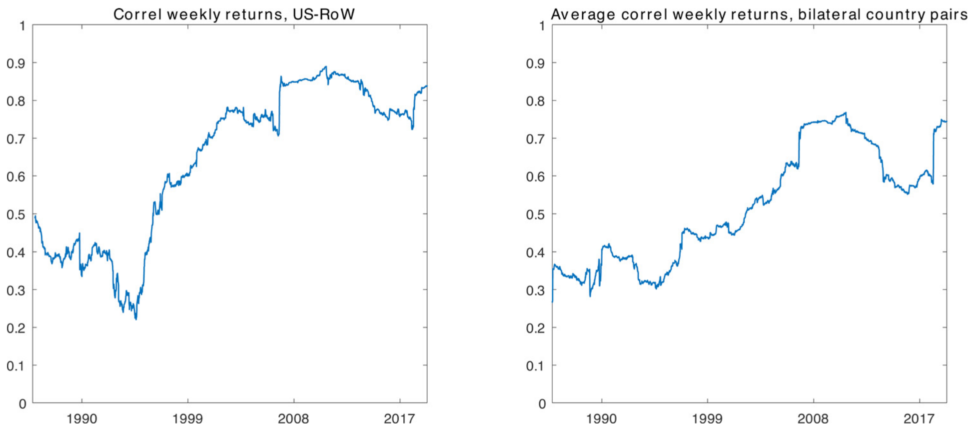

Fig. 1. Stock market correlations. Notes: Left panel shows the correlation $SMC_{US,RoW} = corr(\mathbf{r}_t^{US}, \mathbf{r}_t^{RoW})$ of weekly returns of MSCI US and MSCI World excl. US, over four- year rolling windows. Right panel shows the average of bilateral stock market corre- lations $SMC_{ij} = corr(\mathbf{r}_i^t, \mathbf{r}_j^t)$ for 21 developed economies (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK and USA), using the weekly returns of their MSCI indices, over four year rolling windows. The stock market correlations are dated at the middle week of the four year rolling windows. Data range 01/01/1984–23/07/2021. Data sources: Bloomberg and Eikon Refinitiv.

1. Introduction

In the post WW2 period, the cross-country correlations between the stock markets in developed economies were fairly low, implying significant potential benefits from diversification. Beginning in the mid 1990s, stock market correlations started increasing and continued to do so up until the aftermath of the Great Recession. These increases have been quantitatively large; for example the correlation of US equity returns with the equity returns in an aggregate index of other developed economies has risen from below 0.4 in the 1980s to above 0.8 in the 2010s and a similar pattern emerges when looking at bilateral developed country pairs (see Fig. 1). The increase in stock market correlations has coincided with a concurrent strengthening in foreign direct investment (FDI) linkages between the largest economies with developed equity markets. The aim of this paper is to explore the relationship between these two phenomena.

We propose an intuitive mechanism through which increases in bilateral FDI positions can lead to higher stock market correlations between two countries. Because multinational corporations engage in FDI abroad, they become exposed to country specific TFP shocks in the foreign country. In an environment with increased FDI, firms generate a larger fraction of their earnings abroad. This implies stronger incentives to increase investment in response to shocks in the foreign country. In the presence of intangible technology capital, increased investment abroad can also spill over to investment at home, due to the complementarity between tangible and intangible capital. Investment and capital are therefore more synchronized across multinationals and this implies their equity values are also more correlated.[1]

We first establish an empirical link between the comovement of stock returns with international stock markets and FDI. We provide evidence that the returns of multinational firms comove with foreign stock markets more than the returns of non-multinational firms; this is more so when multinational firms have more intangible assets, or have high R&D expenditure, which is consistent with our theoretical mechanism. Additionally, using a panel of 21 developed economies, we also find that increases in FDI of the order of magnitude observed across these countries, are associated with increases in their bilateral stock market comovement that are sizeable, positive and highly significant, even when controlling for trade.

With this empirical evidence in place, we propose a production-based asset pricing model (see Jermann, 1998) extended to two countries and, crucially, incorporating multinational firms investing in technology capital as in McGrattan and Prescott (2010). To quantify the importance of the mechanism, we add country-specific shocks, introduce incomplete international asset markets and calibrate the model to two regions, the US and the rest of the world. We find that the observed increase in FDI positions leads to a rise in stock market correlation from 0.380 to 0.520, accounting for one third of the overall observed increase.

When markets are incomplete, a firm's FDI operations provide access to foreign markets and, at the same time, offer diversification benefits for its shareholders. The model assigns FDI an important role in explaining stock market comovements, even when abstracting from the diversification channel. To show this, we recompute our experiments assuming a complete set of contingent claims available to shareholders. In that case, firms' investment decisions are decoupled from portfolio diversification considerations. We find that the *level* of stock market correlation increases as markets become more complete, as expected. However, the *increase* in stock market correlation when FDI linkages are strengthened is present for *all* asset market structures, including the two extremes of complete markets and financial autarky. This is despite the fact that the

[1] Key for this mechanism is that intangible capital of the parent firm of the multinational is utilized by both the parent and foreign affiliates. Bilir and Morales (2020) offer direct evidence in support of this.

correlation of dividends can be quite different across market structures and can go up or down in response to the FDI increase, depending on the degree of market incompleteness. Thus, the divergence between the comovement of dividends and the comovement of equity prices, highlighted in Jordà et al. (2019), can be rationalized in our model by incomplete markets. The key insight from the production asset pricing model is that equity price comovements must reflect comovement in investment and capital across multinationals, but can be entirely independent of dividend comovements.

Concurrently with the increase in FDI, the US experienced moderate increases in cross-border equity holdings, as well as in goods trade with other developed economies. Our work also sheds light on the contribution of those two changes to the stock market comovement. Consider first cross-border equity holdings. In contrast to standard models of diversification as in Heathcote and Perri (2004, 2013) where FDI and portfolio diversification are treated as interchangeable, our model allows for a distinction and thus a non-trivial interaction between the two. When we introduce cross-border equity holdings to the model, and allow them to rise exogenously at the same time as FDI and in line with the data, this does not generate additional increases in the stock market correlation. We also extend our model to allow for trade as in McGrattan and Waddle (2020). In our setup, trade and FDI are substitutes reflecting the focus of the model on horizontal FDI between developed economies.[2] As a result, an increase in trade tends to decrease FDI and hence stock market correlation. Thus, in our experiments, increased trade does not contribute to stock market comovement either.

The mechanism we propose highlights a key role for FDI in explaining stock market correlation over and above any indirect effects it might have through inducing GDP synchronization. Our calibration exercise suggests that increased GDP synchronization could have also played a role. To the extent that this synchronization is itself a result of higher FDI, the role of FDI could potentially have been larger than captured by our model. A small but significant effect of FDI on GDP correlations is found in Cravino and Levchenko (2017) and in Menno (2017).[3] Cravino and Levchenko (2017) show this using firm-level data and rationalize their finding in a model based on Melitz (2003). Their model includes labor supply fluctuations and a rich structure of shocks, but abstracts from investment and capital dynamics. In contrast, we abstract from some of those features, but incorporate investment and capital dynamics and argue these are crucial for understanding equity price comovement. Such dynamics are also included in Menno (2017) but, like Cravino and Levchenko (2017), his focus is on business cycles synchronization and not equity prices. Following a similar logic, trade could also have had an indirect effect on stock market correlation through more synchronized business cycles. Baxter and Kouparitsas (2005) argued that trade can indeed drive business cycle synchronization. Furthermore, at least part of the trade effect operates through multinational production sharing and vertical FDI, as discussed in Burstein et al. (2008), di Giovanni and Levchenko (2010), di Giovanni et al. (2018) and Zlate (2016) amongst others. All of this work focuses on business cycle synchronization whereas our framework focuses on the effects of FDI on stock market comovement, abstracting from its effects on GDP correlations. Our model is an extension of the model proposed in McGrattan and Prescott (2010) and used in Anagnostopoulos and Atesagaoglu (2020); Kapička (2012) and Menno (2017) amongst others. Similarly to Helpman et al. (2004) the focus is on horizontal FDI, but in contrast to that paper it also incorporates the dynamics of investment and capital which are crucial for understanding equity price comovements.[4] The novel contribution of our paper is that we use this dynamic FDI model to study cross-country stock market comovement.

On the empirical side, the observation that cross-country stock market correlations increased since the mid 1990s has been documented in a number of papers. Goetzmann et al. (2005) were amongst the first showing that there has been a dramatic increase in global stock market correlations starting early 1990s. Along the same lines, Quinn and Voth (2008) argue that the observed increase is attributed to greater capital market openness. Claessens et al. (2011) document the same fact and contrast this finding to the fact that there has been no notable change in the cross-country correlations of credit and house prices. Viceira and Wang (2018) attribute the increase in stock market correlations to financial globalization, which has made discount rate shocks significantly more correlated across markets, while they argue that trade globalization does not seem to play a role. Jordà et al. (2019) also document the increase in global equity price synchronization since the 1990s. Interestingly, they find that investment comovement also reached a peak in the mid 2000s, a result consistent with the prediction of our model, namely that higher FDI openness leads to an increase in both investment and stock market correlations. They focus on the role of US monetary policy in coordinating the global appetite for risk as an additional explanation of stock market comovement going beyond the synchronization of investment whereas, our focus is on quantifying the effect of FDI and the resulting investment synchronization. More recently, Gavazzoni and Santacreu (2020) highlight the importance of R&D spillovers as a potential driver for increased international stock market comovement.

2. Stock market comovement and FDI: Empirical evidence

We first provide descriptive evidence on the evolution of global stock market correlations and FDI linkages over the past four decades. We then formally establish the empirical relationship between FDI and stock market comovements in two

[2] This is consistent with the model and evidence in Helpman, Melitz (2003). See Ramondo and Rodriguez-Clare (2013) for a more recent discussion of FDI and trade, and the circumstances under which they are substitutable (horizontal FDI) or complementary (vertical FDI).

[3] The relation between financial integration and business cycles synchronization is ambiguous, see Backus et al. (1992), Imbs (2004), Heathcote and Perri (2004), Cesa-Bianchi et al. (2019), Kalemli-Ozcan et al. (2013) and Kalemli-Ozcan et al. (2013).

[4] An important alternative model of FDI is developed in Ramondo (2014). Antras and Yeaple (2014) provide a detailed review of various modelling approaches on FDI.

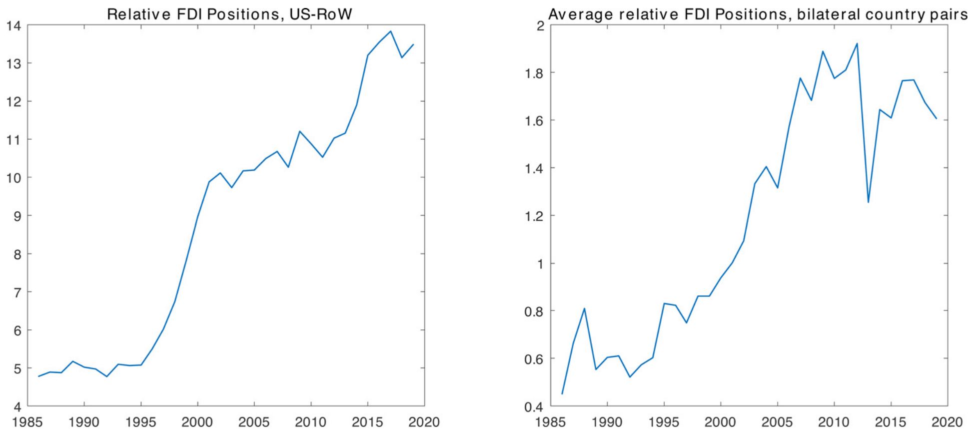

Fig. 2. Relative FDI positions. Notes: The relative FDI position for countries i and j in year t is defined as $R_{Fij,t} = \frac{FDI^j_{i,t}+FDI^i_{j,t}}{GDP_{i,t}+GDP_{j,t}}$, where where $FDI^j_{i,t}$ is the FDI position of country j in country i, $FDI^i_{j,t}$ is the FDI position of country i in country j, and $GDP_{i,t}$ and $GDP_{j,t}$ denote the country GDPs, all in million USD. Left panel shows $RF_{US,RoW}$. Right panel shows the average of bilateral RFij for 21 developed economies (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK and USA). All data are yearly and RF is expressed in %. Data range 1986–2019. Data Source: OECD Statistics.

ways, first using a panel of bilateral country pairs, and second using a cross-section of firms. The former analysis offers evidence of a positive association of FDI and stock market comovement over and above what can be attributed to increased trade and business cycle synchronization. The latter reaffirms the country level results at a disaggregated level and confirms that intangible capital is key for our proposed mechanism by allowing us to test whether the comovement of stock returns is stronger for multinationals that rely more on R&D and intangible capital.

Starting with stock markets, our data consists of MSCI Indices for the developed economies that are included in MSCI World.[5] We first look at the stock markets in the US, and compare to the rest of the world, using MSCI US and MSCI World excl. US, then look at all bilateral correlations using MSCI indices for 21 countries included in MSCI World. We use the MSCI indices to first calculate week-on-week returns for a country i at the end of week t as $r_{it} = \left(MSCI_{it} - MSCI_{i,t-1}\right)/MSCI_{i,t-1}$ and then calculate a measure of comovement $SMC_{ij,t}$ between the stock markets of countries i and j at time t, using the definition $SMC_{ij,t} = corr\left(\mathbf{r}^i_t, \mathbf{r}^j_t\right)$, where $\mathbf{r}^i_t = (r^i_{t-w/2}, \ldots, r^i_{t+w/2})$, with w a pre-specified time 'window'. Using a rolling window of $w = 208$ weeks (four years), the left panel of Fig. 1 shows correlations between the US and the rest of the world, and the right panel shows the average bilateral correlations of all bilateral country pairs, for data that ranges from 1984 to 2021. Each point reported in this graph shows the middle of the rolling window used for calculating the reported correlation. The left panel of Fig. 1 shows that there has been a substantial upshift in the correlation between US and the rest of the world, starting in the mid 1990s. The average correlation of weekly returns for the decade 1986 to 1995 is 0.368 and the one for 2006 to 2015 is 0.825. The right panel of Fig. 1 confirms that the substantial increase in correlations is not only a US phenomenon but can be seen at the bilateral level too.

We define a measure of FDI linkages between two countries i and j at the start of year t relative to the size of the two economies, as in Kalemli-Ozcan et al. (2013):

$$RF_{ij,t} = \frac{FDI^j_{i,t} + FDI^i_{j,t}}{GDP_{i,t} + GDP_{j,t}}, \tag{1}$$

where $FDI^j_{i,t}$ is the FDI position of country j in country i, $FDI^i_{j,t}$ is the FDI position of country i in country j, and $GDP_{i,t}$ and $GDP_{j,t}$ denote the country GDPs, all in million USD. In Fig. 2, the left panel shows the measure of relative FDI, RF between the US and the rest of the world, and the right panel shows the average relative FDI from all bilateral pairs of the 21 countries, all in %. During the 1980s and well into the 1990s, the FDI between the US and the rest of the world was stable and around 5% of world GDP. Starting in the mid-90s, the FDI measure increases steadily reaching double the size by 2015 at approximately 10% and increasing further to about 13% more recently. The right panel of Fig. 2 shows a similar trend for the average relative FDI positions between the 21 countries, which has more than doubled over the same time period. Comparing Figs. 1 and 2 suggests that these increases in FDI have coincided with the period of increased average correlation of returns.

[5] The MSCI World consists of the following 23 countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, UK and USA. For our empirical analysis and calibration, we exclude Singapore and Hong Kong. Data sources: Bloomberg and Refinitiv Eikon.

Table 1
Stock market returns and FDI, country-pair panel data.

Method	smc$_{ij}$ (1) FE	smc$_{ij}$ (2) FE	smc$_{ij}$ (3) FE	smc$_{ij}$ (4) FE	smc$_{ij}$ (5) FE	smc$_{ij}$ (6) MG	smc$_{ij}$ (7) CCEMG	smc$_{ij}$ (8) CCEMG
ln (RF)	.1649***	.1576***	.0751***	.0174**		.1161***	.0632**	.0589**
	(.0300)	(.0285)	(.0101)	(.0082)		(.0383)	(.0820)	(.0251)
ln (RFL)					.0051***			
					(.0018)			
ln (RT)		.0858	.1856***	.0009	.0023	.1309***	-.0432	.0480
		(.0549)	(.0542)	(.0242)	(.0172)	(.0289)	(.0558)	(.0388)
trend			.0093***					.0006
			(.0030)					(.0016)
time FE				yes	yes			
# Obs.	3321	3321	3321	3321	2582	3295	3295	3283
# Groups	189	189	189	189	186			
R^2	.2082	.2167	.3037	.6288	.6303			
$p > \chi^2$						.0000	.0770	.0235

Notes: The panel consists of country pairs of 21 developed countries (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK and USA), over the period 1985–2019, in yearly frequency. The dependent variable smc_{ij} is the correlation of 52 week-on-week returns of the MSCI indices of two countries i and j in a given year. RF denotes relative FDI positions; RFL denotes relative FDI flows; RT denotes relative trade. Cols (1)–(5): Panel specifications are estimated with country pair fixed effects; Driscoll-Kraay standard errors with max lag 4 reported in parentheses. Cols (6)-(8): Averages of heterogeneous slopes are estimated with Mean Group estimator (MG) in (6) and with Common Correlated Effects Mean Group estimator (CCEMG) in (7) and (8). Pesaran-Smith standard errors reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% level respectively. Data sources: *Eikon*, *Bloomberg*, *OECD Statistics* and *ComTrade*.

Panel evidence at the country-pair level. Our panel consists of variables of interest for country pairs, at yearly frequency, for the period 1985 to 2019. We construct a yearly measure of stock market comovement between two countries i and j in year t, denoted by $smc_{ij,t}$, by calculating the correlations of 52 week-on-week returns between the MSCI indices of the two countries in the given year t. Our remaining data consists of yearly bilateral FDI positions and flows, and GDPs from OECD, and bilateral trade flows from the database of the Center for International Data from UC Davies and ComTrade. We construct the measure of relative FDI as in Eq. (1), and a measure of relative trade defined as $RT_{ij,t} \equiv \left(IM^j_{i,t} + EX^j_{i,t}\right)/\left(GDP_{i,t} + GDP_{j,t}\right)$, where $IM^j_{i,t}$ and $EX^j_{i,t}$ denote imports and exports respectively from country j to country i. Table 1 presents the main estimation results. Columns (1)–(5) report results from the following empirical specification:

$$smc_{n,t} = \alpha_n + \lambda_t + \gamma_F * \ln RF_{n,t} + \gamma_T * \ln RT_{n,t} + \varepsilon_{n,t}, \tag{2}$$

where n indexes a country pair (we have data for $N = 189$ country pairs). We allow for country-pair fixed effects α_n, as well as time fixed effects λ_t, or a time trend. The reported Driscoll-Kraay standard errors with four lags take into account potential cross country pair correlation, heteroskedasticity and serial autocorrelation.[6] The coefficient on FDI remains positive and highly significant across specifications, including controlling for trade, allowing for a trend, controlling for time fixed effects and using FDI flows instead of stocks. In addition, it remains significant when we allow for slope heterogeneity across bilateral pairs using Pesaran and Smith (1995) mean group (MG) estimator as well as accounting for common factors using Pesaran (2006) common correlated effects mean group (CCEMG) estimator.[7]

In our benchmark estimation in column (2), we find that doubling RF is associated with an increase of 0.157 in stock market correlation even after controlling for trade. In light of our model in the next section, we view this as an association that is likely to be driven, at least to some extent, by an underlying common factor relating to globalization and financial liberalization. This is indeed confirmed when we include a trend or a time fixed effect or account for common correlated effects, all of which reduce the size of the estimated direct effect of FDI. In the model section we argue that globalization drives up stock market correlations specifically through increasing FDI linkages and that other aspects of globalization pertaining to increases in trade and portfolio diversification have less of an effect.[8] Firm level data can provide more direct evidence on causality.

Cross-sectional evidence at the firm level. We now investigate the relationship between stock price correlations and FDI using cross-sectional, firm-level data. Our main hypothesis is that stock prices and returns of publicly quoted companies

[6] The implementation of Driskoll and Kraay (1998) standard errors was based on Hoechle (2007). Kang and Pflueger (2015) follow a similar approach in a different context of country financial panel data.

[7] The implementation of MG and CCEMG estimations is based on Eberhardt (2012).

[8] Among other robustness checks, we control for relative trade in *intermediate* goods, and find that the effects of FDI survive, despite the effect from intermediate trade being larger and more significant. Trade in intermediate goods is important for international comovements, as shown by Huo et al. (2019) and Jiang and Richmond (2019). Results are reported in the Online Appendix.

Table 2
Summary statistics for stock market returns and FDI, cross-section of firms.

	$fsub = 0$			$fsub = 1$			
Averages, 2016-19	mean	std. dev.	freq	mean	std. dev.	freq	$p > F$
correl	0.2223	0.1131	641	0.3101	0.1361	1559	0.0000
ifa_ta	0.2014	0.2193	421	0.2729	0.2069	1310	0.0000
ifa_tfa	0.2942	0.3004	418	0.4482	0.3016	1298	0.0000
rdsb	0.0463	0.2103	691	0.2990	0.4579	1605	0.0000
beta	0.9334	0.5403	641	1.1491	0.4599	1559	0.0000
rev (bn USD)	1.2051	2.8595	683	6.4527	23.5006	1595	0.0000
num employees	4898	12,996	503	19,514	75,473	1408	0.0000
tangibles (th USD)	1,860,214	6,370,382	682	2,694,373	11,549,249	1585	0.0763
intangibles (th USD)	543,647	1,855,436	421	2,902,834	11,470,193	1310	0.0000
earnings (th USD)	166,781	575,923	683	653,661	2,732,029	1589	0.0000

Notes: Cross sectional data based on averages from years 2016–2019. Sample size = 2296 firms incorporated in the US. Cols 1–3 are for firms with no foreign subsidiaries, $fsub = 0$; cols 4–6 are for firms with foreign subsidiaries, $fsub = 1$, i.e. multinationals. *correl* is the correlation of a firm's weekly returns with MSCI World ex. US; *ifa_ta* is intangible fixed assets over total assets; *ifa_tfa* is intangible fixed assets over total fixed assets; *rdsb* is a dummy variable that takes the value 1 if the firm belongs to the European Commission R&D Scoreboard 2019 and 0 otherwise; *beta* is the firm's beta, calculated as $covar(r^i, r^{US})/var(r^{US})$, where r^i and r^{US} are are weekly returns for firm i and MSCI US respectively, for the period 2016-19; *rev* is firm's revenues in billion USD; *num employees* is firm's number of employees; *tangibles* is total tangible assets in thousands USD; *intangibles* is firm's intangible assets in thousand USD; *earnings* is firm's earnings in thousand USD. Column 7 reports p-values for testing whether the two means are statistically indistinguishable. Data sources: *Eikon*, *Bloomberg*, *Orbis* and *European Commision R&D Scoreboard*.

with no foreign subsidiaries will correlate less with foreign stock markets than those of companies with foreign subsidiaries. Our model in the next section provides a mechanism through which this can work and the mechanism assigns a key role to intangible technology capital used by multinationals. To investigate this mechanism more closely, we also consider a second hypothesis, namely that multinational firms that engage in more R&D and/or intangible capital investment should have stock returns that correlate more with international stock markets.

Our data is from Orbis and consists of 2296 currently active firms in the US corporate sector that are listed in the main US stock exchanges, i.e. NYSE and NASDAQ, with ordinary and registered shares for a four-year period of Jan 2016 to Dec 2019. We consider firms from this dataset to be multinational, if they have any foreign subsidiaries. Table 2 provides summary statistics for the firms in our sample, grouped by whether they are multinationals ($fsub = 1$) or not ($fsub = 0$). The top rows of the table show summary statistics for the variables we use in our regression analysis. The first variable, denoted by *correl*, is the correlation of a firm's weekly returns with MSCI World ex. US. On average, this correlation is almost 50% higher for firms with foreign subsidiaries than those without. Next, we consider three measures of intangible investment of a firm, namely (i) intangible fixed assets over total assets (ifa_ta), average of yearly data over 2016-19; (ii) intangible fixed assets over total fixed assets (ifa_tfa), average of yearly data over 2016–19; and (iii) a dummy variable that takes the value 1 if the firm belongs to the R&D Scoreboard 2019, published by the European Commission (*rdsb*). All these measures are higher for firms with foreign subsidiaries than those without. Additionally, our controls include (iv) the firms' betas for the same period, in order to capture comovement of firms' returns with international stock markets that is potentially over and above any comovement of the US market with the rest of the world markets, (v) the firms' average revenues over 2016–19, to control for firm size and (vi) industry dummies based on the NAICS 2 digit classification.[9] The last few rows of Table 2 give additional summary statistics pertaining to the size of firms in the sample including the number of employees, tangible and intangible assets, and earnings. In our dataset, firms with foreign subsidiaries, i.e. multinationals, are larger (higher revenues, higher earnings and larger number of employees) than firms without foreign subsidiaries. They also tend to have returns that are more volatile than the market returns ($beta > 1$), while firms without foreign subsidiaries have returns that are less volatile than the market ($beta < 1$). Fig. 3 shows the breakdown of firms by industry.

Our empirical specification is

$$correl_i = \text{cons.} \; + \; \alpha \times fsub_i \; + \; \beta \times intang_i + \; \gamma \times (fsub_i \times intang_i) + \text{controls}, \tag{3}$$

where *intang* stands in for one of the three measures of intangible investment described above, i.e. ifa_ta, ifa_tfa or *rdsb*. In Table 3 we report results for several versions of the above specification. For each specification (see columns 1, 2, 3, 4), we report a version of the regression where we control for industry and cluster standard errors by industry in columns marked with (b). First, we note that betas and revenues have significant effects on correlations and these are quite stable across specifications. Also, industry dummies improve the model's explanatory power. Even controlling for these, columns (1a) and (1b) show, as a first pass, that multinational firms have significantly higher correlations with MSCI World ex. US than firms with no foreign subsidiaries.

[9] Using 4 digit-level industries does not change our main conclusions, see the Online Appendix.

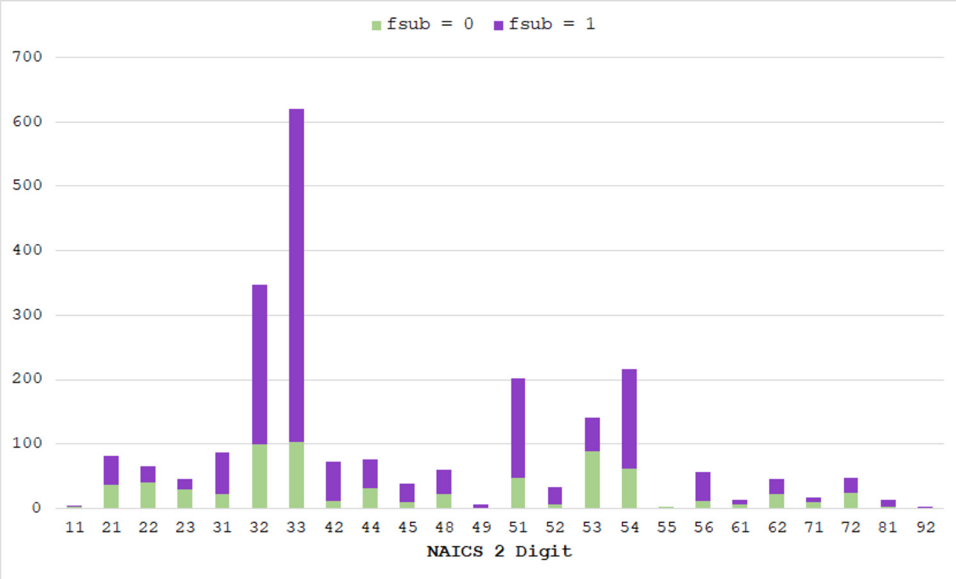

Fig. 3. Firms in data set by industry, based on NAICS 2 digit codes. Notes: Number of firms in sample of 2296 firms by NAICS 2-digit industries and fsub = 0 (light green) and fsub = 1 (dark purple). The variable f_{sub} takes the value 1 if the firm has foreign subsidiaries (i.e. is a multinational), and 0 otherwise. NAICS 2-digid codes: 11 Agriculture, Forestry, Fishing and Hunting; 21 Mining; 22 Utilities; 23 Construction; 31–33 Manufactur- ing; 42 Wholesale Trade; 44–45 Retail Trade; 48–49 Transportation and Warehousing; 51 Information; 52 Finance and Insurance; 53 Real Estate Rental and Leasing; 54 Professional, Scientific, and Technical Services; 55 Management of Companies and Enterprises; 56 Admin- istrative and Support and Waste Management and Remediation Services; 61 Educational Services; 62 Health Care and Social Assistance; 71 Arts, Entertainment, and Recreation; 72 Accommodation and Food Services; 81 Other Services (except Public Administration); 92 Public Administration. Data Source: Orbis. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Stock market returns and FDI, cross-section of firms.

	$correl_i$		$correl_i$		$correl_i$		$correl_i$	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
intang var	n/a	n/a	ifa_ta	ifa_ta	ifa_tfa	ifa_tfa	rdsb	rdsb
fsub	.0610***	.0657***	.0325***	.0405**	.0257***	.0341*	.0422***	.0492***
	(.0053)	(.0126)	(.0089)	(.0177)	(.0096)	(.0192)	(.0056)	(.0088)
intang			-.0417**	-.0008	-.0425**	-.0145	-.0304**	.0099
			(.0263)	(.0388)	(.0165)	(.0249)	(.0138)	(.0123)
fsub × intang			.1324***	.1068**	.1024***	.0852**	.0918***	.0629***
			(.0272)	(.0435)	(.0199)	(.0349)	(.0152)	(.0110)
beta	.1124***	.1225***	.1353***	.1360***	.1340***	.1349***	.1061***	.1163***
	(.0058)	(.0175)	(.0077)	(.0131)	(.0079)	(.0133)	(.0058)	(.0162)
rev	.0010***	.0011**	.0009**	.0011*	.0009**	.0010*	.0010***	.0010**
	(.0003)	(.0004)	(.0003)	(.0005)	(.0003)	(.0005)	(.0003)	(.0003)
constant	.1126***	.0977***	.1058***	.0929***	.1118***	.0979***	.1204***	.1008***
	(.0066)	(.0220)	(.0090)	(.0222)	(.0092)	(.0205)	(.0066)	(.0206)
NAICS-2		yes		yes		yes		yes
# Obs.	2190	2190	1667	1667	1652	1652	2190	2190
R^2	.2651	.3424	.3122	.3639	.3102	.3620	.2960	.3812

Notes: Cross sectional data based on averages from years 2016–2019. Sample size = 2296 firms incorporated in the US. *correl* is the correlation of a firm's weekly returns with MSCI World ex. US; *fsub* is 0 for firms without foreign subsidiaries and 1 with firms with foreign subsidiaries, i.e. multinationals. The third line, *intang var*, specifies which control variable was used as a proxy for investment in intangible technology capital: *ifa_ta* is intangible fixed assets over total assets; *ifa_tfa* is intangible fixed assets over total fixed assets; *rdsb* is a dummy variable that takes the value 1 if the firm belongs to the European Commission R&D Scoreboard 2019 and 0 otherwise. *beta* is the firm's beta, calculated as $covar(r^i, r^{US})/var(r^{US})$, where r^i and r^{US} are are weekly returns for firm i and MSCI US respectively, for the period 2016-19; *rev* is firm's revenues in billion USD. NAICS-2 = yes indicates that two digit NAICS industry dummies were included in the specification. Robust standard errors reported in parentheses in columns (1a), (2a), (3a) and (4a). Standard errrors are clustered by two digit NAICS industry in columns (1b), (2b), (3b), (4b). ***, ** and * denote significance at 1%, 5% and 10% level. Data sources: *Eikon*, *Bloomberg*, *Orbis* and *European Commision R&D Scoreboard*.

Our main focus is on results in columns (2)–(4) where a measure of intangibles is included. With these specifications, we can gauge the effect of being a multinational ($\alpha + \gamma \times intang_i$), as well as the additional effect that intangible capital has on correlations conditional on a firm being a multinational (γ). In those, the interaction term is always significant. Interestingly, having a lot of intangibles alone does not seem to increase correlations unless this is combined with being a multinational. This is exactly what our theoretical model captures. In terms of the size of the effects, even though the coefficients on $fsub$ and on the interaction term vary somewhat across specifications, we note that the combined effect is stable across specifications. For example, looking at column 4, a multinational ($fsub = 1$) that is also part of the R&D Scoreboard ($rdsb = 1$) has on average a correlation with world stock markets that is 0.10–0.11 larger than a non-multinational that is not part of the R&D Scoreboard. This size remains similar whether one controls for industry or not. Similar effects are implied by the specifications in columns (2) and (3), for which the *intang* variables are continuous.

3. A two-country asset pricing model with multinational firms

Our model extends McGrattan and Prescott (2010), by adding country-specific productivity shocks and capital adjustment costs, and allowing for incomplete international asset markets. Time is discrete and infinite, indexed by $t = 0, 1, 2, \ldots,$. There are two countries, each populated by a representative household, and two multinational firms. Each multinational firm operates two productive units (plants), one located within the country where the multinational is incorporated and one located abroad, i.e. there are four plants overall. Superscripts $h = 1, 2$ denote the multinational that *owns* the plant and subscripts $i = 1, 2$ denote the country in which the plant is *located*. We assume that firm h is incorporated in country h.

Firms. Consider the plant located in country i and owned by multinational firm h. Its output at time t is denoted by Y_{it}^h, and the tangible capital stock and labour used for this production are denoted by K_{it}^h and N_{it}^h respectively. Each multinational also has technology (intangible) capital M_t^h which is used as an additional input to production in both of its plants, hence no i subscript. The production technology of multinational h in country i is given by $Y_{it}^h = A_i Z_{it} \sigma_i^h (\upsilon_i M_t^h)^{\alpha_M} (K_{it}^h)^{\alpha_K} (N_{it}^h)^{\alpha_N}$, where α_K, α_M and α_N denote, respectively, the income shares of tangible capital, intangible capital and labor, $0 < \alpha_K, \alpha_M, \alpha_N < 1$ and $\alpha_K + \alpha_M + \alpha_N = 1$. A_i is a productivity level parameter, Z_{it} is a country-specific productivity (TFP) shock and σ_i^h are parameters governing the degree of FDI openness of each country i. We normalize $\sigma_1^1 = \sigma_2^2 = 1$ and assume that $0 < \sigma_1^2, \sigma_2^1 < 1$. As in McGrattan and Prescott (2010), $\sigma_i^h < 1$ reflects exogenous barriers preventing firm h from taking full advantage of FDI opportunities in country i. In the calibration, these are used to capture the amount of production by the foreign affiliate relative to the home firm in country i. The term υ_i captures the number of locations available for setting up plants in country i and will be proxied by population size in country i in our calibrations. Capital accumulations are described by

$$K_{it+1}^h = (1 - \delta_K) K_{it}^h + X_{K,it}^h - \Phi\left(X_{K,it}^h / K_{it}^h\right) K_{it}^h, \; i, h = 1, 2, \tag{4}$$

$$M_{t+1}^h = (1 - \delta_M) M_t^h + X_{M,t}^h - \Phi\left(X_{M,t}^h / M_t^h\right) M_t^h, \; h = 1, 2, \tag{5}$$

where $X_{K,it}^h$ and $X_{M,t}^h$ are investment in tangible and technology capital respectively, δ_K and δ_M are depreciation rates and Φ is the capital adjustment cost function, in line with Hayashi (1982). Multinational h maximizes its expected discounted sum of dividends $\mathbb{E}_0 \sum_{t=0}^{\infty} \Psi_{0,t}^h D_t^h$ where $\Psi_{0,t}^h$ is the stochastic discount factor used by the firm. Dividends D_t^h are given by

$$D_t^h = Y_{1t}^h + Y_{2t}^h - W_{1t} N_{1t}^h - W_{2t} N_{2t}^h - X_{K,1t}^h - X_{K,2t}^h - X_{M,t}^h. \tag{6}$$

Households. The representative household in each country i maximizes $\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \ln c_{it}$, where c_{it} is the consumption of household i.[10] Each country i is populated by υ_i identical individuals so that aggregate consumption in country i is $C_{it} \equiv \upsilon_i c_{it}$ and aggregate supply of labour to the plants that operate domestically is $N_{it} \equiv \upsilon_i n_{it}$, where n_{it} is the labor supply of household i, which we assume to be inelastic. Households earn a wage W_{it} and can trade shares of the domestically incorporated firm only.[11] The number of shares bought by each household at time t and the price at which they are bought are denoted by θ_{it+1} and Q_t^i respectively. The total number of shares bought at time t in country i is $\upsilon_i \theta_{it+1}$. As a benchmark, we assume that markets are incomplete (IM) and allow households to only trade a non-contingent bond b_{it} across countries. The budget constraint is then

$$c_{it} + Q_t^i \theta_{it+1} + Q_{b,t} b_{it+1} + \frac{\chi}{2} b_{it+1}^2 = W_{it} n_{it} + \left(D_t^i + Q_t^i\right) \theta_{it} + b_{it}. \tag{7}$$

where $Q_{b,t}$ is the bond price at t and bond holdings are subject to a quadratic adjustment cost. We also consider two extreme international asset market structures, namely financial autarky (FA) and complete markets (CM). In the FA economy, we do not allow cross-country trade in financial assets by households, as in Heathcote and Perri (2002).[12] The budget

[10] The choice of log utility is not crucial for our results, see the Online Appendix for alternative preference specifications.

[11] This assumption of perfect home bias is relaxed in Section 5.

[12] Notice, however, that this is not strict financial autarky since firms can still engage in FDI and expose their shareholders to the economic conditions of the foreign country.

constraint is

$$c_{it} + Q_t^i \theta_{it+1} = W_{it} n_{it} + \left(D_t^i + Q_t^i\right)\theta_{it}. \tag{8}$$

In the CM economy, households can trade a full set of state contingent claims. The budget is

$$c_{it} + Q_t^i \theta_{it+1} + \int q_t\left(s^t, \bar{s}\right) b_{it+1}\left(s^t, \bar{s}\right) d\bar{s} = W_{it} n_{it} + \left(D_t^i + Q_t^i\right)\theta_{it} + b_{it}\left(s^{t-1}, s_t\right), \tag{9}$$

where s^t denotes the history of shocks $\left(Z_1^t, Z_2^t\right)$, $b_{it}\left(s^{t-1}, s_t\right)$ is the number of contingent claims bought in the previous period at state s^{t-1} and promising to pay at state $s^t = \left(s^{t-1}, s_t\right)$ today and $q_{t-1}\left(s^{t-1}, s_t\right)$ is the corresponding price. When markets are complete, the intertemporal marginal rates of substitution are equalized across all households (of both countries), and this defines the stochastic discount factors for both firms. When markets are not complete, since we have assumed perfect home bias, the stochastic discount factor of firm h corresponds to the intertemporal marginal rate of substitution of the representative household in country h.

Market clearing. Labour markets clear in each country, so that $N_{it} \equiv \upsilon_i n_{it} = N_{it}^1 + N_{it}^2$, $i = 1, 2$. The aggregate supply of shares of each firm is normalized to one and the stock market clears in each country, $\upsilon_i \theta_{it} = 1$, $i = 1, 2$. Additionally, under incomplete markets, we assume that bonds are in zero net supply and the world bond market clears, i.e. $\upsilon_1 b_{1t+1} + \upsilon_2 b_{2t+1} = 0$. Finally, under complete markets, the contingent claims markets clear, that is $\upsilon_1 b_{1t+1}\left(s^t, \bar{s}\right) + \upsilon_2 b_{2t+1}\left(s^t, \bar{s}\right) = 0$ for all $\bar{s}$ and all s^t. The following world aggregate resource constraint holds $\sum_{i=1}^2 C_{it} + \sum_{h=1}^2 \left(X_{K,1t}^h + X_{K,2t}^h + X_{M,t}^h\right) = \sum_{i=1}^2 \sum_{h=1}^2 Y_{it}^h$. Under IM the left hand side of the resource constraint also includes aggregate bond holding costs $(\chi/2)\sum_{i=1}^2 \upsilon_i b_{it+1}^2$.

4. Quantitative results

Calibration. We calibrate the model in quarterly frequency, to match long run ratios based on US data and only make countries asymmetric with respect to the levels of GDP, population sizes and the fraction of firm tangible capital installed in the foreign plant (FDI).[13] The income shares α_K, α_M and α_N along with the depreciation rates δ_K, δ_M and the discount factor β are calibrated as follows. Using NIPA data for the US corporate sector between 1982 and 1995, we compute the average labor share to be $\alpha_N = 0.636$ and the average ratio of corporate tangible investment to corporate GDP to be 0.14, which pins down δ_K. We follow McGrattan and Prescott (2010) and Kapička (2012) in setting the depreciation rate of technology capital to 8% annually, so that $\delta_M = 0.020$. Using *Fixed Asset Tables*, we calculate the tangible capital to output ratio in the corporate sector to be 6.8 for the same years and use the discount factor to target this in our benchmark economy. The relative size of technology to tangible capital is estimated to be approximately 0.333 in Kapička (2012) and this can be matched by choosing $\alpha_K = 0.276$ in our model. We normalize the US values of population and productivity to one, i.e. $\upsilon_1 = A_1 = 1$. We then take country 2 to be the *rest of the world*, as defined by the set of 21 countries used in Section 2. Using OECD data for 1991–1995 we find that the population of these countries is 2.160 times the US population and thus set $\upsilon_2 = 2.160$. We also find the sum of the GDPs of these countries to be 1.75 times that of the GDP of US, and therefore calibrate $A_2 = 0.822$ to match the relative GDPs.

Capital adjustment costs are commonly used in international macro models to avoid excessive investment volatility. Accordingly, in our model, tangible and intangible capital are subject to adjustment costs and we assume that $\Phi(x) = \phi(x-\delta)^2/2$, where the adjustment cost parameter ϕ is calibrated to match the observed standard deviation of tangible capital investment relative to the standard deviation of output for the US economy. We target the value of 2.390 for this ratio, reported by Boldrin et al. (2001).[14]

Turning to the productivity shocks, we follow Backus et al. (1992); Baxter and Crucini (1995) and Kehoe and Perri (2002), and assume that the shocks $Z_t = (Z_{1t}, Z_{2t})^T$ follow a vector autoregressive (VAR) process of the form $Z_{t+1} = \Psi Z_t + \varepsilon_{t+1}$, where $\psi_{11} = \psi_{22} \equiv \rho_1$ is a common persistence parameter and $\psi_{21} = \psi_{12} \equiv \rho_2$ is a spillover parameter. The innovations $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})^T$ are serially independent, multivariate normal random variables. We set $\rho_1 = 0.95$ and $\rho_2 = 0$, using the estimates of Baxter and Crucini (1995) and Kehoe and Perri (2002). The variances of the innovations are calibrated such that the model matches the average standard deviations of US real GDP and rest of the world real GDP for the years 1962–1995. We set the correlation of the innovations to 0.268 to match the average correlation between US real GDP and real GDP of each of the 21 countries in the MSCI index, which we compute to be 0.256 between 1976 and 1995.

We calibrate the FDI openness parameters σ_1^2, σ_2^1 to capture respectively the FDI position in the US (FDIUS) and the US direct investment position abroad (USDIA) first in the early 1990s (*Before*) and then for early 2010s (*After*). For this, we use Flow of Funds data from the Federal Reserve Board, and find that the ratio of FDIUS to the tangible capital stock owned by US corporations in the US (USIUS) was $K_1^2/K_1^1 = 0.12$ on average during 1991–1995. For the same period, we find that the ratio of USDIA to USIUS was $K_2^1/K_1^1 = 0.15$. We match these two quantities in our benchmark calibration by choosing $\sigma_1^2 = 0.792$ and $\sigma_2^1 = 0.840$ (*Before*). In our main experiments we then change these values to $\sigma_1^2 = 0.877$ and

[13] As pointed out by McGrattan and Prescott (2010) domestic production in the model has to be adjusted by subtracting technology investment to match to measured GDP in the BEA data $GDP_{it} \equiv Y_{it}^1 + Y_{it}^2 - X_{Mt}^i$. We do so in our calibration and denote measured GDP in the Tables as GDP_i.

[14] Contrary to all other parameters, the adjustment cost parameter value has to be adjusted to obtain the same target for each of the three economies we consider (FA, IM and CM).

Table 4
Correlations of model simulated variables.

	Financial Autarky		Incomplete Markets		Complete Markets	
	Before	*After*	*Before*	*After*	*Before*	*After*
$corr\left(r^1, r^2\right)$	0.335	0.472	0.380	0.520	0.643	0.823
$corr(Q^1, Q^2)$	0.338	0.478	0.370	0.511	0.644	0.824
$corr(X^1, X^2)$	0.338	0.478	0.370	0.511	0.641	0.822
$corr(K^1, K^2)$	0.339	0.477	0.359	0.496	0.650	0.827
$corr(D^1, D^2)$	-0.211	-0.564	-0.023	-0.451	0.804	0.928
$corr(C_1, C_2)$	0.335	0.429	0.358	0.453	1.000	1.000
$corr(GDP_1, GDP_2)$	0.259	0.242	0.256	0.239	0.220	0.194
$corr(X_{K,1}, X_{K,2})$	0.343	0.451	0.368	0.452	0.558	0.617

Notes: Correlations of stock returns r, stock returns prices Q, total firm investment X, total firm capital K, firm dividends D, country consumptions C, GDP and country tangible capital investment X_K, when FDI is calibrated to the 1990s (*Before*) and the 2010s (*After*), under Financial Autarky, Incomplete Markets and Complete Markets.

$\sigma_2^1 = 0.921$, so that the deterministic model's steady state capital ratios change to $K_1^2/K_1^1 = 0.31$ and $K_2^1/K_1^1 = 0.50$ and match the corresponding numbers in the data for the years 2011–2015 (*After*). Finally, in the incomplete markets model we choose the bond cost parameter $\chi = 0.033$ to match the cross-country stock return correlation $corr\left(\mathbf{r}_t^i, \mathbf{r}_t^j\right) = 0.387$, where now stock returns are defined as quarter-on-quarter for the period 1986–1995, over four year rolling windows.

Results. Our baseline experiment involves exogenously increasing the FDI openness parameters σ_i^h to match the increase in FDI positions observed in the data and using the model to obtain the implied increase in the stock market correlation. Table 4 presents correlations of returns, stock prices and other key variables in the stationary distribution of the economy before and after the changes in σ_i^h.[15] Under the benchmark calibration with incomplete markets, the correlation of quarterly stock returns is 0.380 before the FDI openness increase and it increases to 0.520 after the increase. In the data, the correlation increases from 0.387 to 0.809. Thus the FDI channel alone explains approximately *one third* of the increase in stock market correlation.

To understand stock price comovement, it is helpful to relate the stock price of a firm to its capital and investment. In the Online Appendix, we derive the following equilibrium condition

$$Q_t^h = \frac{1}{1 - \Phi'\left(X_{K,1t}^h / K_{1t}^h\right)} K_{1t+1}^h + \frac{1}{1 - \Phi'\left(X_{K,2t}^h / K_{2t}^h\right)} K_{2t+1}^h + \frac{1}{1 - \Phi'\left(X_{M,t}^h / M_t^h\right)} M_{t+1}^h, \tag{10}$$

which expresses the ex-dividend value of firm h as a weighted sum of its capital stocks. In a standard RBC model with no FDI and no intangible capital, there is only one capital stock and it is valued at a price q arising from the presence of adjustment costs just like in this model. This is commonly referred to as Tobin's q. Here, similar capital stock valuations arising from adjustment costs are derived, but they can potentially be different for the different types of capital. As is standard, these capital stock valuations arise due to adjustment costs and are increasing in the investment rates of the corresponding capitals. Using this equilibrium relation, and noting that to a first order approximation, the stock price of a firm is the weighted average of the total capital stock and the total investment of the firm, we can relate the correlation of stock prices to the comovement of the *total capital stocks* $K_t^h \equiv K_{1t}^h + K_{2t}^h + M_t^h$, as well as the comovement of the similarly defined *total investments* X_t^h of the two firms. Table 4 illustrates that the correlation of investment is very similar to the correlation of the capital stocks and both are very similar to the correlation of stock prices. Therefore, stock price comovement can be attributed to synchronization of investment across the two multinationals.

Guided by this observation, we can see how stock prices tend to comove when foreign firms are exposed to domestic shocks through FDI. A persistent increase in home TFP induces the foreign multinational to increase its investment at the same time as the home multinational, because its foreign plant is now expected to be temporarily more productive. This increased investment has a positive effect on the accumulation of both the tangible capital of the foreign firm in the home country and the intangible capital of the foreign firm. Depending on the level of exposure and the size of the shock, the increased investment may also induce an increase in tangible capital of the foreign firm in the foreign country, due to the complementarity with intangible capital. Therefore, the higher the FDI exposure is, the larger the stock price correlation is. Key to this channel is the presence of intangible technology capital, without which the effect on the foreign capital of the foreign firm is absent.[16]

To analyze the interaction between investment and stock prices for the two multinational firms, we consider impulse responses to a one standard deviation increase in the TFP of the home country, Z_1, under the assumption that $corr(\varepsilon_{1t}, \varepsilon_{2t}) = 0$. Impulse responses of the stock prices, investment and dividends of the two firms are shown in Fig. 4. Solid lines represent

[15] Moments are generated using a simulation of 100,000 periods of the third order local approximation of the model, from which we drop the first 1000 periods and then take averages. All series are HP filtered with a smoothing parameter of 1600, for calibration at quarterly frequency.

[16] In our model 19% of the gross return to US parent R&D is from affiliates located in the RoW, a feature consistent with the findings in Bilir and Morales (2020).

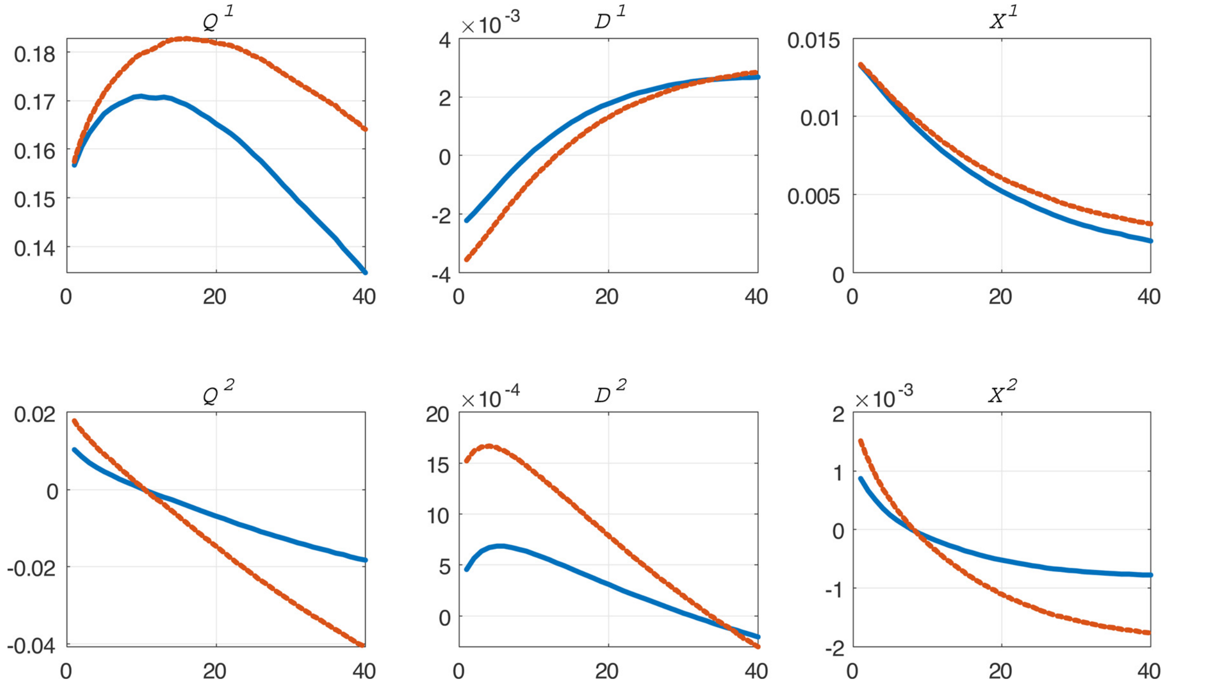

Fig. 4. Model impulse response functions, under Incomplete Markets. Notes: Shock is one standard deviation increase in the TFP of country 1, assuming $correl(\varepsilon_{1t}, \varepsilon 2t) = 0.Q^h, D^h$ and X^h denote stock price, dividends total investment respectively for firm $h = 1, 2$. Blue solid line is the economy Before; red dotted line is the economy After. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

responses in the low FDI environment (*Before*) and dotted lines responses in the high FDI environment (*After*). The initial impact of the TFP increase is to increase overall production in country 1, i.e. both Y_1^1 and Y_1^2. The effect is exactly symmetric on the two plants located in country 1, which implies a symmetric increase in labor demand by the two plants. Because labour supply is inelastic at the country level, wages in the home country increase and there is no re-allocation of labor across the two plants on impact. The effect is to increase the current operating profits for firm h, i.e. the right hand side of the firm financing constraint $D_t^h + X_t^h = Y_{1t}^h - W_{1t}N_{1t}^h + Y_{2t}^h - W_{2t}N_{2t}^h$. The effect is larger for the home (country 1) firm, since most of its production and cash flow comes from the home plant and smaller for the foreign (country 2) firm since its plant abroad (in country 1) is small relative to its plant in its own country. Importantly, this asymmetry in the size of the cash flow effect on the two firms becomes smaller as FDI increases.

Firm investment responds for two reasons: the direct effect is due to the TFP shock persistence, which implies higher expected TFP for the corresponding plants and increases the return to investment. This prompts both firms to increase investment generating the positive investment correlation. A second effect arises due to a smoothing motive and operates via the firm's stochastic discount factor which, in equilibrium, is equalized to the marginal rate of substitution of households owning the firm. Specifically, depending on the availability of other risk sharing opportunities for the firms' owners, the foreign firm might adjust its investment and dividend choice to provide some smoothing for its owners. Thus the comovement of investment and of dividends will depend on the underlying asset market structure and, in particular, dividends may be negatively correlated across firms, as the numerical results in Table 4 indicate.

To further understand how these two channels affecting the stock price comovements operate, it is instructive to consider the two extreme cases of financial autarky and complete markets using the results from Table 4. First, we note that when markets are complete, stock prices comove more closely both before and after the change, but there is still a sizeable increase from 0.644 to 0.824 as a result of the increase in FDI openness. Under financial autarky, stock prices comove less overall, but the increase is still present and of similar magnitude going from 0.340 to 0.478. Investment responds to a positive shock Z_1 more symmetrically across firms when markets are complete, because perfect insurance ensures marginal rates of substitution, and hence firms' discount factors, are perfectly synchronized across countries. In the absence of insurance possibilities (FA), because the stochastic discount factors of the two firms are not synchronized, the stock price correlation is lower. Nevertheless, these numerical results suggest that the effect of increased expected returns to investment dominates, and therefore investment and hence stock market correlation are positive and increasing in FDI openness, irrespective of the comovement of dividends.

An alternative way to look at stock prices is by reference to the usual asset pricing equation, which relates the stock price to the expected discounted sum of dividends, where the firm's discount factor reflects shareholders' marginal rate of substitutions. It is tempting to infer stock price comovement by looking at the correlation of dividends and the correlation of stochastic discount factors, but this can be misleading. Both the covariance of the marginal rate of substitution with foreign firm dividends and the serial correlation of both these variables would need to be taken into account, and this makes it harder to obtain a simple intuitive explanation using this approach. It is nevertheless interesting to highlight the behavior of dividends in our model, as this is an observable that is often used to analyze the sources of equity price comovements (see, for example, Viceira and Wang, 2018 and Jordà et al., 2019). In our model dividends are *positively correlated* when markets are complete and their correlation increases as FDI increases. In contrast, if markets are sufficiently incomplete, dividends can be *negatively correlated* and become even more so as FDI increases. Despite this, stock returns are still positively correlated and that correlation increases with FDI regardless of the financial market structure or the sign of the dividend correlation.

In summary, a production based asset pricing model ties stock prices to investment and, with more FDI exposure, multinationals respond positively and by more to foreign shocks. This implies an increase in the stock market correlation. Looking at the correlation of dividends can be misleading as a means of inferring stock price comovement. If anything, the level and change in the correlation of dividends are more relevant for inferring the level of international asset market completeness, and could potentially be used as a test of market completeness.[17]

5. A model extension with portfolio diversification and trade

We now introduce portfolio diversification and trade to the model and show that, at least in this context, these two candidates have limited ability to explain increases in cross-country stock market correlations. Even though the home bias in stock holdings is a well-documented fact, assuming *perfect* home bias, is somewhat extreme. In practice, there were some cross border holdings of equities in the beginning of the 1990s and, more importantly, there was an increase in cross-border holdings from the 1990s to the 2010s. For the US economy, according to the *Reports on Foreign Portfolio Holdings of US Securities* produced jointly by the Federal Reserve Board, the NY Fed and the Treasury, the fraction of US equities held by foreigners in 1994 was 5.1% and the corresponding average for the years 2011–2015 was 13.6%. Our extended model below allows for cross-border equity holdings and considers the effects of an exogenous increase in these holdings.

A second potentially relevant change during this period has been the increase in global trade. As a rough measure, we use FRED data to compute US exports plus imports as a fraction of GDP in the US for the periods 1991–1995 and 2011–2015 and find the ratios to be 0.206 and 0.298 respectively. To incorporate trade in the model, we follow McGrattan and Waddle (2020). In particular, we assume that the four plants produce differentiated goods and denote the producer prices by P_i^h for $i, h = 1, 2$. Consumers in each country can buy three goods: the good produced at home by the home multinational, the good produced at home by the foreign multinational and the good produced abroad by the foreign multinational and imported to home. The elasticity of substitution between the home multinational good c_{it}^i and a composite of the two goods produced by the foreign multinational $c_{it}^{h\neq i}$ is denoted by ρ, i.e. $c_{it} = \left[\left(c_{it}^i\right)^{(\rho-1)/\rho} + \left(c_{it}^{h\neq i}\right)^{(\rho-1)/\rho}\right]^{(\rho-1)/\rho}$. Consumption of the foreign multinational's composite good $c_{it}^{h\neq i}$ is given by a CES aggregator $c_{it}^{h\neq i} = \left[\left(c_{it}^{h\neq i,F}\right)^{(\varrho-1)/\varrho} + \left(c_{it}^{h\neq i,T}\right)^{(\varrho-1)/\varrho}\right]^{\varrho/(\varrho-1)}$. Here, $c_{it}^{h\neq i,F}$ denotes the consumption by consumers in country i of the good produced by $h \neq i$ within country i, so that F stands for *FDI*. Similarly, $c_{it}^{h\neq i,T}$ denotes the consumption by consumers in country i of the good produced by $h \neq i$ abroad and imported into country i, so that T stands for *Trade*. The elasticity of substitution between those two is denoted by ϱ. The usual price aggregators define P_{it}, the price of the composite consumption good c_{it}. Because of the presence of linear (iceberg) transportation costs ζ_i, the consumer price of the imported good in country i is given by $P_i^{h\neq i,T} = (1+\zeta_i)P_{h\neq i}^{h\neq i}$. The household budget is now

$$P_{it}c_{it} + Q_t^1\theta_{it+1}^1 + Q_t^2\theta_{it+1}^2 + Q_{b,t}b_{it+1} + \frac{\chi}{2}b_{it+1}^2 = W_{it}n_{it} + \left(D_t^1 + Q_t^1\right)\theta_{it}^1 + \left(D_t^2 + Q_t^2\right)\theta_{it}^2 + b_{it}. \quad (11)$$

In addition to the consumption price P_{it}, the budget also differs from our benchmark model in that households in country i hold shares θ_{it}^h in both $h = 1$ and $h = 2$ firms. That is, we allow households to hold a diversified portfolio. Stock market clearing requires now that $\upsilon_1\theta_{1t+1}^h + \upsilon_2\theta_{2t+1}^h = 1, \quad h = 1, 2$. Solving the model with a portfolio choice for households is beyond the scope of our paper. We instead aim to obtain a sense of the effects of diversification by making a simplifying assumption: households can only trade shares of their home firm. As a result, shares of firm h are priced in the market using the country h marginal rate of substitution. We use this market value as the objective of the firm, which is consistent with the notion that portfolio investment, as opposed to FDI, does not endow the investor with significant influence over firm decisions.[18] An important implication of our simplifying assumption is that, in equilibrium, the fraction of each firm

[17] Marcet and Scott (2009) use a similar idea to test for market completeness in government debt markets by looking at contradictory implications of complete and incomplete markets models for debt persistence and for the covariance of debt and deficit.

[18] With incomplete markets and heterogeneous shareholders, unanimity on the firm's objective cannot be guaranteed (Carceles-Poveda and Coen-Pirani, 2009). Our choice is also consistent with a majority rule since in our calibrations the home households are indeed a large majority of the shareholders.

Table 5
Correlations of model simulated variables, other factors.

	Before	*After all incl*	No υ	No A	No λ	No ζ
$corr(r^1, r^2)$	0.385	0.527	0.533	0.531	0.556	0.584
$corr(Q^1, Q^2)$	0.347	0.515	0.521	0.519	0.546	0.571
$corr(X^1, X^2)$	0.347	0.500	0.506	0.504	0.531	0.549
$corr(K^1, K^2)$	0.387	0.534	0.540	0.538	0.563	0.602
$corr(D^1, D^2)$	-0.207	-0.582	-0.588	-0.587	-0.526	-0.597
$corr(C_1, C_2)$	0.314	0.366	0.369	0.368	0.390	0.353
$corr(GDP_1, GDP_2)$	0.259	0.234	0.233	0.233	0.231	0.270
$corr(X_{K,1}, X_{K,2})$	0.324	0.413	0.413	0.413	0.425	0.441

Notes: Correlations of stock returns r, stock returns prices Q, total firm investment X, total firm capital K, firm dividends D, country consumptions C, GDP and country tangible capital investment X_K, when the model is calibrated to 1990s (*Before*) and to 2010s (*After, all incl*), under Incomplete Markets. Cols (3)–(6) report correlations from counterfactual experiments where the corresponding parameter is at its *Before* level.

held by home (and foreign) households is fixed as in Fogli and Perri (2015). To be concrete, let λ_i^h be the total number of shares of firm h held by households in country i so that $\lambda_1^2 \equiv \upsilon_1\theta_{1t+1}^2$ and $\lambda_2^1 \equiv \upsilon_2\theta_{2t+1}^1$ denote the total cross-border equity holdings. With the total number of shares of each firm outstanding normalized to one, λ_i^h is also the fraction of shares of firm h held by households in country i, i.e. market clearing implies $\sum_i \lambda_i^h = 1,\ \ h = 1, 2$. In this case, the equilibrium budget constraints are

$$P_{it}c_{it} + Q_{b,t}b_{it+1} + \frac{\chi}{2}b_{it+1}^2 = W_{it}n_{it} + D_t^i\frac{\lambda_i^i}{\upsilon_i} + D_t^{h\neq i}\frac{\lambda_i^{h\neq i}}{\upsilon_i} + b_{it},\ \ i = 1, 2. \tag{12}$$

Households hold a diversified portfolio and their dividend payments are a weighted sum of the two firms' dividends. Furthermore, increases in $\lambda_i^{h\neq i}$ can capture the increased reliance on foreign dividends arising from increased cross-border equity holdings.

We maintain the same benchmark calibrated targets as in the previous section.[19] We follow McGrattan and Waddle (2020) in choosing $\rho = 10$ and $\varrho = 100$, the latter intended to capture a high substitutability between the FDI and trade goods produced by the same firm. We choose a symmetric transport cost $\zeta = 0.186$ to match a ratio of exports plus imports over measured GDP of 0.206 for the US. We also assume that the equity home bias is symmetric across the two countries $\lambda_1^2 = \lambda_2^1 \equiv \lambda^*$. We set the fraction of shares held by foreigners $\lambda^* = 0.051$ in the benchmark case so the fraction held at home is $\lambda = 1 - \lambda^*$. In the experiments we consider, we incorporate simultaneous increases in FDI, trade and cross-border equity holdings, as well as changes in the relative size of the two economies. Specifically, we set $\sigma_1^2 = 0.868$ and $\sigma_2^1 = 0.891$ to match the same FDI increases as in the original experiment, we set $\lambda^* = 0.136$ and $\zeta = 0.052$ to capture the documented increases in cross-border equity holdings and in trade between the US and the rest of world and we also let υ_2/υ_1 drop to 1.950 and A_2/A_1 drop to 0.795 to match the changes in relative population and GDP observed in OECD data in the periods of interest. Table 5 presents the results. The column labelled '*Before*' shows the correlations of variables in the stationary distribution of the model calibrated to the 1990s and the column '*After (all incl)*' shows the same results when all the aforementioned changes are included simultaneously. The rest of the columns consider counterfactual experiments where we maintain one parameter to its ' *Before*' level in order to gauge the effect of each parameter separately.

It is noteworthy that the correlation of stock prices when all changes are included increases from 0.385 to 0.527, which is very close to the result we obtained in Table 4 where only FDI changes were included. To understand why, note first that changes in the relative size of the economies via υ_i and A_i do not affect stock market correlations. This is not entirely surprising given that these parameters mostly affect steady states and the level changes are not dramatic. However, when we switch off the increase in cross-border equity holdings λ, the correlation actually increases even more to 0.556. That is, increased cross-border holdings have a negative effect on the stock market correlation. This is because with incomplete markets, firms' investment behavior is to some extent driven by a desire to provide insurance to their owners. In response to a positive TFP shock in country 1, the insurance effect pushes firms to adjust their dividend responses in opposite directions in order to provide some smoothing, and that induces lower investment correlations. To provide the same level of smoothing through negatively correlated dividend payments, firms have to adjust their dividends more aggressively the closer λ^* is to 1/2. In turn, this leads to even lower correlation of investment. As a result, when λ is higher, the correlation of firm investment and stock prices is lower. If households had a full set of contingent claims available for trade, i.e. under complete markets, the introduction of portfolio diversification would be moot. In that case, firm decisions on dividends and investment are decoupled from cross-country risk sharing considerations. Marginal rates of substitution are equalized across countries

[19] Parameters remain the same as for the baseline model except for minor adjustments due to the presence of trade, see the Online Appendix for more details.

Table 6
Regressions of with data and model simulated data for US and RoW.

	data $smc_{US,RoW}$ (1a)	model $smc_{US,RoW}$ (1b)	data $smc_{US,RoW}$ (2a)	model $smc_{US,RoW}$ (2b)
RFL_t	.1334***	.0916***	.0950**	.0914***
	(.3980)	(.0008)	(.0404)	(.0006)
RT_t			.0861***	.0031***
			(.0258)	(.0002)
Adj R^2	.0516		.1002	
# Obs.	190	190	190	190

Notes: All data are linearly detrended. Data for US and RoW are in quarterly frequency, from 1970Q1 to 2017Q2. Correlations $smc_{US,RoW}$ in cols (1a) and (2a) are based on q-o-q returns over 4-year rolling windows. Correlations $smc_{US,RoW}$ in Cols (1b) and (2b) use model-simulated data, all calibrated to quarterly frequencies. *RFL* is relative FDI flows and *RT* is relative trade. *, ** and *** show significance at 1%, 5% and 10% level respectively. Data sources: *OECD Statistics*, *FRED*, *BEA Fixed Asset Tables*, *Bloomberg*.

state-by-state, and the portfolio composition is indeterminate and irrelevant for stock price comovement. However, as we saw in the previous section, it is still the case that FDI plays a significant role, since it directly affects the synchronization of investment across firms. We view this as an important takeaway, namely that FDI can matter over and above any risk sharing role that it might play, and this clearly distinguishes FDI from household portfolio diversification in this model in contrast to standard models of diversification as in Heathcote and Perri (2004, 2013).

Increased goods trade is also found to have a negative effect on the stock market correlation, albeit for a different reason. To understand why, we first note that there is an important interaction between the trade cost parameter and the FDI openness parameters, since there is high substitutability between the two corresponding goods. This is intended to capture the idea that a firm can access foreign markets for its good either by exporting more or by producing more in their FDI plant. When transport costs decrease, firms substitute away from FDI production and increase exports. As a result, to rationalize the observed increase in FDI, the underlying reduction in barriers to FDI must be larger in the presence of falling transport costs than in the absence thereof. Thus, our calibration in this extended model features an even larger increase in the FDI openness parameters σ_i^h compared to our benchmark model. When we shut down the transport cost change, FDI increases by more than in the data and, as a result, the stock market correlation increases by more to 0.571.

An alternative way to compare quantitatively our model mechanism to the data is to run similar regressions in the model and data. To this end, we consider detrended time series data for the US versus the RoW for the period 1970Q1 to 2017Q2 and regress correlations of quarterly returns of MSCI US and MSCI World ex. US on relative FDI flows (RFL_t) and relative trade (RT_t). For the model regressions, we first generate 190 steady states after calibrating σ_{12}, σ_{21} and ζ to match the data time series of FDIs and trade for each of the quarters in the same period. Keeping all our other parameters constant at the values calibrated to the '*Before*' scenario, we simulate our model for 10,000 periods for each of the 190 calibrations and we calculate the correlation of quarterly stock returns over the long simulation. We then run the same regressions with detrended model generated data as we did with the data, and compare the outcomes in Table 6.[20] The coefficients on FDI are remarkably similar in model and data, meaning the extended model is capturing the quantitative relationship well.

To summarize, the effect on stock market comovement of the shift in FDI survives the addition of all the additional factors; even though globalization has brought about increases in trade and cross-border equity holdings concurrently with the increase in FDI, in the model these additional factors do not seem to explain the remaining increase in the stock market correlation, after the increase in FDI has been taken into account. Globalization has arguably also brought about increased business cycle synchronization, which could be another factor explaining the stock market comovement increase. To investigate this, as a final experiment, we mechanically increase the correlation of TFP shocks to gauge the extent to which business cycle synchronization could explain the remaining difference. For the years 1996–2015, we compute the average correlation between US real GDP and real GDP of each of the countries in the MSCI index to be 0.610 (compare to 0.256 in our benchmark calibration). Starting from our full model, we increase $corr(\varepsilon_{1t}, \varepsilon_{2t})$ to match this increase in GDP correlations and find the stock price correlation increases further from 0.527 and up to 0.787. We conclude that increased business cycles synchronization is likely to have played an important role too, but we note that part of the observed increased business cycle synchronization could also be due to the increase in FDI.[21] Our model however abstracts from this additional indirect channel, in order to focus on the direct effects of FDI on stock market correlation, over and above any effects through business cycles synchronization.

[20] For more details on this exercise, see the Online Appendix.
[21] See, Cravino and Levchenko (2017) and other references in the introduction in support of this view.

6. Closing comments

Cross-country stock market correlations have seen a sharp rise in the past 30 years. This paper establishes a relationship between this rise and the increase in FDI positions in the last thirty years, both empirically and theoretically. The timing of the observed increase in stock market correlations coincides with the sharp increase in FDI positions among large developed economies that has taken place from the mid 1990s onwards. A positive relationship between stock market correlation and FDI is found to be present even when controlling for other potentially contributing factors.

Our theoretical framework is rich enough to provide a meaningful calibrated asset pricing model of the US economy versus the rest of the world, yet parsimonious enough to be able to disentangle the channels that matter for the comovements of the two stock markets. There are two key elements of the model that are important for establishing the link between FDI and stock markets: first the multinational firms, that engage in foreign direct investment, and second the presence of intangible technology capital in the production functions of the firms. With these two in place, we show that the comovement of investment can drive to a significant extent the comovement in stock prices. In our benchmark calibration, FDI was found to generate approximately one third of the observed rise in stock market comovement. We have argued that in the context of our model, neither increased trade nor increased portfolio diversification alone can help explain the stock market correlation increase. Factors contributing to business cycles synchronization as well as coordination of the global appetite for risk through US monetary policy, as argued in Jordà et al. (2019), are two candidates for explaining the remaining increase.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2022.05.005.

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