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Time-varying exchange rate pass-through into terms of trade ☆

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ABSTRACT

The U.S. invoices nearly all of its imports and exports in U.S. dollars. The U.S. terms of trade should therefore be "neutral" to movements in the U.S. dollar against other currencies. However, I find that the U.S. dollar pass-through into the U.S. terms of trade is: (i) on average positive and significant (31%); and (ii) it exhibits persistent time variation in the range of 10–60% over the period of 1990–2018. I argue that this can be explained by the changing primary commodity share in U.S. imports and the fact that commodity prices are invoiced, but not always "sticky", in U.S. dollar terms. Without primary commodities, such as petroleum and crude oil, pass-through roughly halves and becomes relatively stable over time. Unlike trade in manufactured goods and services (i.e. non-commodities), trade in commodities thus preserves the conventional link between the exchange rate, terms of trade, and the current account.

1. Introduction

The price of a good that is bought and sold for in U.S. dollars should generally be unrelated to the movements in the value of other currencies. It is only when its price upon sale is invoiced in dollars, but originally set and remains sticky in euros, for instance, that exchange rate pass-through is not zero. In the aggregate, some prices are invoiced and "sticky" in dollars, while others are invoiced in dollars, but sticky in euros or other currencies. The degree to which U.S. prices respond to exchange rate movements therefore depends not on the share of prices invoiced in dollars, but on the share of prices that are sticky in dollars.

In this paper, I study whether or not the observable shares of invoicing currency for imports and exports in the United States (U.S.) can accurately predict how much the aggregate U.S. import and export prices adjust in response to exogenous movements in the U.S. dollar. This would be the case if all prices that are invoiced in U.S. dollars are also sticky in U.S. dollars terms. I choose the U.S., because it is a special country that pays for around 97% of its foreign imports and sells around 90% of its exports to the rest of the world in U.S. dollar terms (Gopinath and Rigobon (2008)). Moreover, the U.S. dollar trade invoicing patterns hardly changed throughout the period of 1995–2014 (Gopinath (2015)).

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Taken at face value, these figures suggest that if the prices of U.S. imports and exports are sticky in U.S. dollar terms, then exogenous U.S. dollar depreciations would cause the U.S. import (export) prices to increase only by around 10% (3%). The U.S. terms of trade, measuring the relative price of imports to exports, would thus deteriorate only by around 7%. It follows that exchange rate pass-through into the U.S. terms of trade should be close to zero and relatively stable over time.

But it turns out that exchange rate pass-through into the U.S. terms of trade is significantly higher and much less stable over time than implied by these invoicing shares. In particular, I show that during the 1990–2018 period, the average exchange rate pass-through is 31%. Furthermore, it decreases from 60% in 1990 to 15% in 2003, then rises back to 60% in 2008 during the peak of the Great Recession, and then gradually reverts to 10% by 2015.

This result suggests that a considerable share of prices that are invoiced in U.S. dollars are not actually sticky in U.S. dollar terms. But it is not immediately clear if this criticism applies to all U.S. imports and exports across the board or just particular sectors. Interestingly, the U.S. micro-level price data studied by Bils and Klenow (2004) shows that primary commodity prices in U.S. dollar terms adjust far more frequently and on average by more than non-commodity prices (i.e. manufactured goods and services).

Guided by these micro-data estimates, I re-estimate exchange rate pass-through into the U.S. non-commodity terms of trade and find that its magnitude roughly halves (i.e. equal to 15%) and becomes much more stable over time. While the average pass-through remains significantly higher than implied by the invoicing shares, the absence of pass-through time variation for non-commodity prices suggests that invoicing shares are reasonably accurate proxy for some sectors. This last result brings further validity to the ubiquitous Dominant Currency Paradigm (DCP) of Gopinath et al. (2020), which characterises the international monetary system as one that revolves around the global U.S. dollar invoicing patterns. But DCP explicitly abstracts from the import and export prices of primary commodities.

Given their volatile nature, it may not seem all that surprising that primary commodity prices generate on average higher and time-varying pass-through into the U.S. terms of trade. But the fact that pass-through varies so much more than the invoicing shares warrants further investigation. After all, nearly 25% of all U.S. imports and 9% of all U.S. exports over the period of 1990–2018 were on average primary commodities, the bulk of which are petroleum and crude oil (see Fig. 1). Abstracting from the primary commodity prices in practice may therefore lead us to falsely conclude that the movements in the U.S. dollar are "neutral" even though they are in fact at least in part transmitted into the U.S terms of trade and, by extension, the U.S. current account.

If we then agree that the discrepancy between pass-through and invoicing shares is not just an empirical artefact, but may be relevant for monetary policy, we need to gain a better understanding of what accounts for the time variation of pass-through. On the one hand, if we take a conventional case where all primary commodity export (import) prices are invoiced in U.S. dollars, but sticky in (non-) U.S. dollar terms, otherwise known as Producer Currency Pricing (PCP), then in theory, exchange rate pass-through into the U.S. terms of trade would correspond to the U.S. commodity share of imports. When I test the hypothesis whether such changes in the trade content are related to changes in exchange rate pass-through, I find some empirical support during time periods when there are substantial changes the U.S. commodity share of imports (i.e. structural breaks), such as in the run-up to the Great Recession of 2008–09, but not otherwise.

On the other hand, independent of the changes in the trade content, pass-through into commodity prices themselves may be time-varying. Because the U.S. is a large open economy, its business cycle spills over into the rest of the world, which is in turn strongly correlated with the global boom-bust cycles of primary commodity prices. Movements in the U.S. dollar may therefore have less of an effect on primary commodity prices when the world economy is booming and commodity producer profit margins are relative high compared to when the world economy is dwindling. Indeed, I test the hypothesis of whether the U.S. output gap is related to changes in exchange rate pass-through and find a strong and statistically significant result of *counter-cyclicality*. Specifically, a 1% increase in the output gap leads to around 5% lower exchange rate pass-through into the U.S. terms of trade.

I also study if the time variation of pass-through can be explained by other observable factors, such as the overall U.S. trade openness, measures of value-added in U.S. imports and exports, index of market uncertainty (VIX), the FED policy rate, the U.S. trend inflation, and the direction as well as the size of the broad U.S. dollar movements. With the exception of market uncertainty, I find that none of these additional factors are economically or statistically significant. I conclude that primary commodity prices are largely sticky in U.S. dollar terms during expansions when market uncertainty is low, but in recessionary times when market uncertainty is high, they are sticky in non-U.S. dollar terms.

The rest of the paper is organised as follows. Section 2 compares and contrasts this paper to the related literature. Section 3 introduces the empirical methodology. Section 4 provides a brief description of the dataset. Section 5 presents the empirical results. And finally, Section 6 summarises and concludes.

2. Related literature

This paper is related to several different strands of the literature in international economics and macroeconomics, which I split into two broad categories: (i) the terms of trade and the current account; and (ii) exchange rate pass-through.

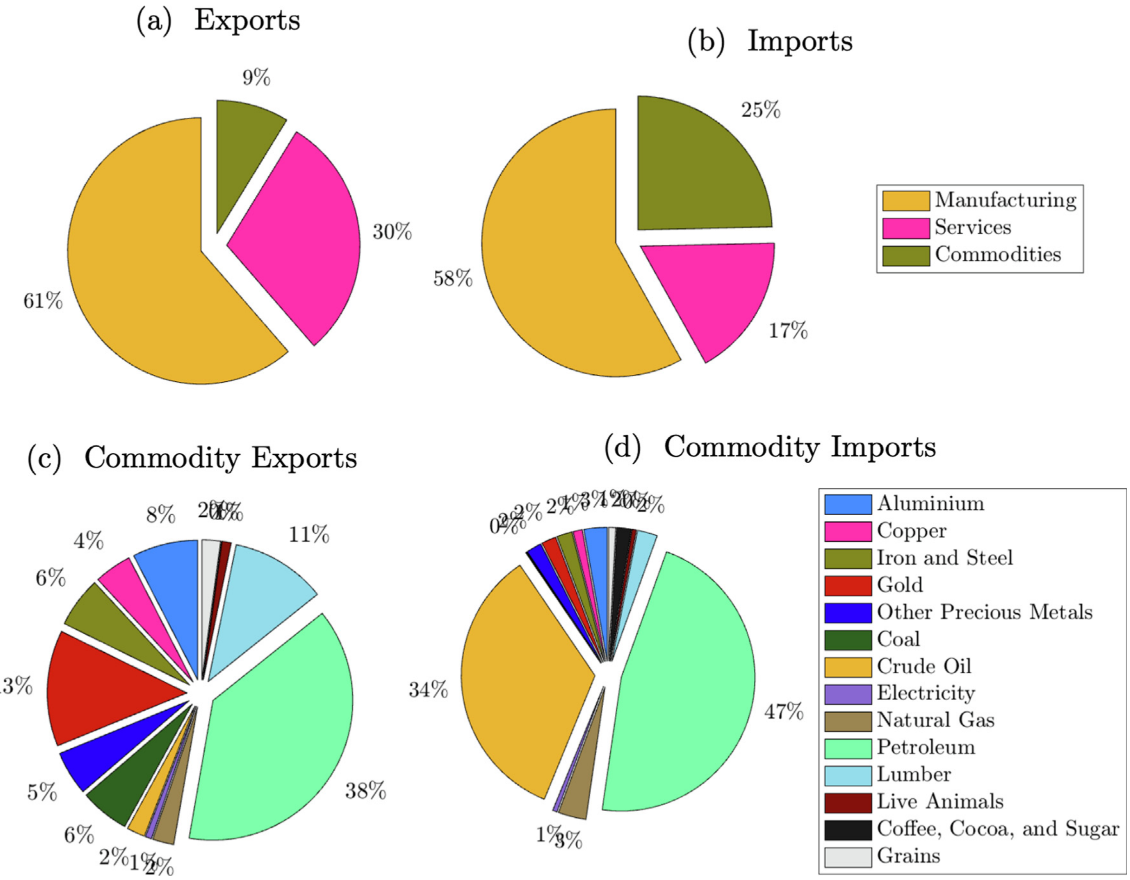

Fig. 1. U.S. Import and Export Breakdown (1990–2018). Note: own calculation using data from the U.S. Bureau of Economic Analysis (BEA).

2.1. Terms of trade and current account

I study the relationship between the U.S. dollar and the U.S. terms of trade without explicitly looking at the aftereffects on the U.S. current account. This is because the relationship between the terms of trade and the current account is much better understood. Yet the link between exchange rate movements and the current account goes all the way back to Harberger (1950), Laursen and Metzler (1950), and later Dornbusch and Fischer (1980). They argue that exogenous currency appreciations improve the domestic terms of trade, such that imports become relatively cheaper to exports, which increases real national income and savings, and thus in turn improves the current account. This became known as the *Harberger-Laursen-Metzler* (HLM) effect. Obstfeld (1982), Svensson and Razin (1983),Persson and Svensson (1985) then emphasise the fact that the relationship between the terms of trade and the current account crucially depends on the persistence and anticipation of the terms of trade adjustments and that permanent or anticipated shocks render the HLM effect obsolete. Since then, Backus et al. (1992),Backus (1993), Backus et al. (1994),Mendoza (1995), and Kose (2002) developed rich terms of trade transmission mechanisms in stochastic small open economy environments. While they attribute terms of trade shocks and the subsequent current account movements to be the major source of business cycle fluctuations in emerging market economies, Schmitt-Grohé and Uribe (2018) and Di Pace et al. (2020) argue that the role of terms of trade shocks may be overstated. But regardless of their role in driving the business cycle dynamics, Otto (2003) and Adler et al. (2018) show that empirically, the relationship between the terms of trade and the current account across countries generally holds and is consistent with the conventional HLM effect. For this reason, throughout the remainder of this paper, I argue that the HLM effect holds as long as the U.S. dollar movements significantly affect the U.S. terms of trade.

2.2. Exchange rate pass-through

There are many studies that measure the extent to which exchange rate movements are reflected in aggregate import prices and aggregate consumer prices. Goldberg and Knetter (1997) and Burstein and Gopinath (2014) provide thorough literature reviews of both the early and the more recent work, respectively. There is also some empirical work that studies exchange rate pass-through into aggregate export prices, such as Choudhri and Hakura (2015). However, I am not aware of any other empirical paper that would study the exchange rate pass-through into the aggregate U.S. terms of trade as a whole. I argue that this may be an oversight in the context of the previous literature on the HLM effect. Because in practice, movements in import prices are positively correlated with movements in export prices, such that measuring pass-through into either separately may generate misleading inference about pass-through into the terms of trade as a whole.

2.2.1. Invoicing currency

The inception of invoicing currency in international economics dates back to the work of Betts and Devereux (1996). They argued that some exporting firms price their goods at the factory door in producer currency units (PCP), such that their prices in foreign currency terms adjust one-to-one with the exchange rate. By contrast, other exporting firms price their goods in the local currency units (LCP) upon arrival at the destination country. Prior to that, much of the work built on the Mundell (1963) and Fleming (1962) paradigm in which all firms adopted PCP. With the advent of invoicing currency data around the world, Goldberg and Tille (2006) and Goldberg and Tille (2008) show that the U.S. dollar plays a special role as a "vehicle" currency in global trade transactions. Following that line of research, Gopinath (2015), Boz et al. (2017),Gopinath et al. (2020), and Mukhin (2022) formalised the so-called Dominant Currency Pricing (DCP) paradigm.

According to DCP, firms especially those domiciled in emerging markets, invoice their exports in U.S. dollars even if they trade with third countries. Movements in the U.S. dollar against their currencies therefore generates higher pass-through than fluctuations of the non-U.S. dollar exchange rates. DCP also predicts that the U.S. import and export prices should largely be invoiced and sticky in U.S. dollars. Gopinath and Rigobon (2008) show that the bulk of U.S. imports and exports are in fact invoiced in U.S. dollars. But this paper shows that exchange rate pass-through into the aggregate U.S. import and export prices is significantly higher and much more time-varying than implied by these invoicing shares.

An extensive line of work argues that the choice of invoicing currency by exporting firms is an endogenous decision (e.g. Friberg (1998), Devereux et al. (2004),Friberg and Wilander (2008), Devereux and Yetman (2010),Gopinath et al. (2010) among others). The more volatile the exchange rate, whatever the cause of that may be, the more likely the firms are to adopt PCP in order to curb the volatility of their offshore profits from exporting measured in domestic currency terms. Engel (2006) was the first to establish an equivalence condition under which invoicing and pricing are synonymous when prices are sticky in the short-run.

This rationale offers one possible explanation as to why exchange rate pass-through into U.S. terms of trade varies over time. As shown by Bils and Klenow (2004), the U.S. non-commodity prices tend to adjust much less frequently, such that invoicing and price setting tend to generally coincide. By contrast, the U.S. commodity prices adjust far more frequently in U.S. dollar terms, which suggests that despite U.S. dollar invoicing, they are more likely to be priced according to PCP. If so, then in theory, exchange rate pass-through into the U.S. terms of trade would correspond to the U.S. commodity share of imports. Consistent with the literature on the endogenous choice of invoicing currency, my results suggest that commodity prices are invoiced and sticky in U.S. dollars while the U.S. economy is booming and market uncertainty is low (i.e. DCP), but when it is dwindling and market uncertainty is high, commodity prices are invoiced, but not sticky in U.S. dollars (i.e. PCP).

2.2.2. Simultaneity

Starting with Campa and Goldberg (2005), numerous empirical studies, including this paper, specify an Autoregressive Distributed Lag (ARDL) type regression model to estimate exchange rate pass-through (e.g. Burstein and Gopinath (2014) and Gopinath (2015) among many others). In these regression models, the dependent variable is some measure of prices, and the list of regressors includes the exchange rate and a number of confounding factors that control for other cost-push and demand-pull pressures.

One concern with the ARDL modelling strategy is that, in theory, prices and exchange rates are determined simultaneously. For instance, if the U.S. dollar fluctuations are transmitted into the U.S. prices, this may cause the FED to set a different interest rate, which in turn feeds back into the broad U.S. dollar. However, the ARDL model treats all exchange rate movements as if they are exogenous. If exchange rates and prices are in fact determined simultaneously, then the ARDL estimates of exchange rate pass-though are subject to the simultaneity bias due to the omitted variables. Devereux et al. (2004) were the first to formalise this concern in a theoretical framework.

While it is true that in many theories of open economy macroeconomics exchange rates and prices are endogenous, in practice, exchange rate movements are to a large extent "disconnected" from the fundamentals. One of the most cited works in this area is Meese and Rogoff (1983), who famously show that the movements in the U.S. dollar against other major currencies are so difficult to predict conditional on various macroeconomic fundamentals deemed relevant by theory that the random walk model tends to perform just as well, if not better. This result then suggests that for all practical intents and purposes, the U.S. dollar fluctuations are close to being random or unpredictable, and thus (weakly) exogenous. More recently, Lilley et al. (2022) show that exchange rate disconnect is "alive and well", though measures of market uncertainty show some potential. I therefore adopt the simplest ARDL specification as the basis for estimating pass-through regressions, but explore the effect of market uncertainty on my estimates of pass-through as one of the robustness checks.

2.2.3. Shock dependence

One fundamental reason why the estimates of pass-through in the literature vary so widely across different countries and different time periods could be because exchange rates and prices respond differently to different types of shocks (e.g. real or nominal). This argument was first asserted by Shambaugh (2008) and later got popularised by Forbes et al. (2018). Their approach addresses both the simultaneity and the shock-dependence properties of pass-through by introducing a Structural Vector Autoregression (SVAR) for exchange rates, prices, and other fundamentals, accompanied by a shock identification strategy that is based on long-run time-invariant structural restrictions informed by theory.

Given that I adopt the ARDL model as the benchmark methodology in this paper, I test whether the time-invariant estimates of pass-through predicted by the ARDL are significantly different from the so-called *unconditional* estimates of pass-through predicted by SVAR. To do so, I build on the work of García-Cicco and García-Schmidt (2020), who show that under certain regularity conditions, the ARDL estimates of pass-through are a weighted average of the shock-dependent pass-through estimates of the SVAR, where the weights correspond to the forecast error variance decompositions. I find that the difference between the two estimates is not statistically significant for the U.S. economy during the 1990–2018 period, which suggests that my estimates of pass-through are not subject to the problem of simultaneity bias. This result is hardly surprising, because as discussed above, exchange rates in practice are disconnected from the macroeconomic fundamentals. That is why over 90% over the variation of the exchange rate upon impact in my estimates of the SVAR are explained by exogenous exchange rate shocks.

2.2.4. Structural time variation

Shocks or no shocks, the structural relationship between exchange rates and prices changes over time. For instance, the U. S. dollar invoicing patterns, the supply chain networks, the global trade openness, and the trade content of the U.S were all fundamentally different at the end of the Bretton Woods era in 1971 than they are today. And thus the aggregate exchange rate pass-through then and now for the exact same type and magnitude of a shock, whatever it may be, is different. The SVAR reliance on the long-run structural restrictions may therefore overstate the relevance of shocks in different periods of time, important though they may be, if it does not account for structural change.

Given the importance of shocks and structural change for pass-through, I choose to extend a simple ARDL model using a state-space approach due to Durbin and Koopman (2012) and Shumway and Stoffer (2016) in order to infer the overall time variation in pass-through, which includes both shocks and structure. My approach does not identify the effects of different types of shocks on pass-through or the relative importance of shocks versus structure. However, in contrast to the previous studies that use the time-invariant ARDL approach, the methodology that I adopt is able to infer not only the time variation of pass-through unconditionally, but also conditionally based on the fluctuations of other observable factors deemed relevant by theory, which is in some ways similar to the shock-dependent SVAR approach. However, due to the computational challenges, I relegate the implementation of a shock-dependent SVAR with an added element of structural change for future research and instead focus on a simple time-varying ARDL model.

There exist other studies of estimating time-varying exchange rate pass-through, such as Ozkan and Erden (2015), who use DCC-GARCH model; Choudhri and Hakura (2006),Cunningham et al. (2017), and Jašová et al. (2019) use the rolling-window regression; and Chou (2019) uses a quantile regression. The closest to my approach is Sekine (2006), who uses a Bayesian state-space approach to estimate time-varying exchange rate pass-through into import and consumer prices in several advanced economies, including the United States.

But unlike these studies, my methodology is able to infer a so-called *conditional* exchange rate pass-through, which offers an answer to not only the question as to "how much" pass-through varies over time, but also "why". In particular, the existing studies of time-varying pass-through use several different methodologies, but in drawing inference they all implicitly assume that changes in pass-through over time are completely random. Then, after they infer the fitted values of pass-through, they project them onto a set of observable factors with the intent of detecting the potential determinants of the time variation (e.g. Ozkan and Erden (2015),Cunningham et al. (2017)). But if changes in pass-through are truly random realisations of the data generating process, then they should be orthogonal to the observable factors when the sample size is sufficiently large. Any sign of a significant structural relationship thus only serves to invalidate the modelling assumptions. To address this criticism, I adopt the state-space methodology, which allows me infer the degree of exchange rate pass-through time variation conditional on observable factors simultaneously, such that the realisation of pass-through is not random, unless I explicitly model it to be random.

2.2.5. Non-linearity

Another strand of the literature on exchange rate pass-through adopts non-linear regression models (e.g. Ben Cheikh (2012),Delatte and López-Villavicencio (2012), Kilic (2016), and Brun-Aguerre et al. (2017) among others). Non-linearity is a type of structural time variation. The literature in this line of research is generally centred around two types of non-linearities: (i) direction (i.e. depreciation versus appreciation of the exchange rate); and (ii) size (i.e. small versus large absolute value change in the exchange rate). I show that the state-space methodology that I adopt is flexible and able to accommodate both types of non-linearities discussed in the literature, and potentially other types of non-linearities, as a special case of the more general model specification. However, I do not find any evidence to support the hypothesis of non-linear pass-through either into the U.S. terms of trade as a whole or into the U.S. import or export prices separately.

3. Methodology

Let the first-order difference in the log terms of trade (TOT) be denoted as $\Delta\tau_t = \tau_t - \tau_{t-1}$, while the first-order difference in the log nominal exchange rate is $\Delta e_t = e_t - e_{t-1}$. Exchange rate pass-through (ERPT) measures "how much" and "how fast" Δe_t is transmitted into $\Delta\tau_{t+h}$, where $h = 0, 1, 2, \ldots$ is the time horizon. ERPT into TOT is zero when the transmission of Δe_t into $\Delta\tau_{t+h}$ is negligible at any time horizon h. ERPT into TOT is said to be *time-varying* when the transmission of Δe_t into $\Delta\tau_{t+h}$ intensifies or subsides over time $t = 1, 2, \ldots, T$ keeping the time horizon h constant (e.g. 4 quarters). ERPT is said to be: (i) short-run when $h = 0$; (ii) medium-run when $0 < h < \infty$; and (iii) long-run when $h \to \infty$. In this section, I explain how I measure ERPT; how I test for the presence or absence of ERPT time variation; and how I determine what drives the time variation, if any, in ERPT.

3.1. Standard Time-Invariant ERPT

Following Campa and Goldberg (2005) and Burstein and Gopinath (2014), the standard way of estimating time-invariant ERPT is using an Autoregressive Distributed Lag (ARDL) model:

$$\Delta\tau_t = \sum_{j=1}^{p} \lambda_j \Delta\tau_{t-j} + \sum_{j=0}^{p} \phi_j \Delta e_{t-j} + \mathbf{z}_t \zeta + \varepsilon_t, \tag{1}$$

where $\varepsilon_t \sim \mathrm{iid}\mathcal{N}(0, \sigma^2)$, $\mathbf{z_t}$ is a vector of control variables including the intercept, and $p \geqslant 0$ is the chosen lag order. I define the *short-run* ERPT using the ARDL coefficient $\phi_0 := \phi$, which captures the effect of an exogenous exchange rate shock on the terms of trade upon impact. I define the *long-run* ERPT as $\sum_{j=0}^{p} \phi_j / (1 - \sum_{j=1}^{p} \lambda_j) := \pi$. This measure takes into the account that the terms of trade may respond to exchange rate changes with a time lag and that the lagged terms of trade response may interact with the lagged exchange rate changes (see the online appendix A for more technical details about measuring ERPT).

3.2. Modelling time-varying ERPT

In order to infer the unobservable time variation of ERPT, I transform the above ARDL model into a state-space (SS) model, which treats coefficients ϕ_t, λ_t, and also ζ_t as latent state variables. Suppose $\mathbf{x}_t = [\Delta\tau_{t-1}, \ldots, \Delta\tau_{t-p}, \Delta e_t, \Delta e_{t-1}, \ldots, \Delta e_{t-p}, \mathbf{z}_t]$ is a $1 \times k$ vector of control variables, $\boldsymbol{\alpha}_t = [\lambda_{t,1}, \ldots, \lambda_{t,p}, \phi_{t,0}, \phi_{t,1}, \ldots, \phi_{t,p}, \zeta_t']'$ is a $k \times 1$ vector of unobservable state variables, $\mathrm{y}_t := \Delta\tau_t$ is the 1×1 measurement variable. I then cast the p-th order ARDL in Eq. (1) in a compact state-space form as follows:

$$\mathrm{y}_t = \mathbf{x}_t \boldsymbol{\alpha}_t + \varepsilon_t, \tag{2}$$

$$\boldsymbol{\alpha}_t = \boldsymbol{\eta} + \boldsymbol{\gamma}\boldsymbol{\alpha}_{t-1} + \boldsymbol{\delta}\mathbf{s}_t + \mathbf{u}_{t-1}, \tag{3}$$

where $k \geqslant 1, \varepsilon_t \sim \mathrm{iid}\mathcal{N}(0, \sigma^2), \mathbf{u}_t \sim \mathrm{iid}\mathcal{N}(\mathbf{0}_k, \boldsymbol{\Xi}), \mathbb{E}[\mathbf{u}_t \varepsilon_t] = \mathbf{0}_k, \mathbf{0}_k$ is a $k \times 1$ vector of zeros, $\boldsymbol{\Xi}$ is a diagonal positive-definite $k \times k$ matrix, $\boldsymbol{\delta}$ is a $k \times q$ matrix for $q \geqslant 1$, and $\mathbf{s}_t$ is a $q \times 1$ vector of observable determinants of the unobservable state $\boldsymbol{\alpha}_t$.

The closed-form solutions to the SS model parameters $\sigma, \boldsymbol{\eta}, \boldsymbol{\gamma}, \boldsymbol{\delta}$, and $\boldsymbol{\Xi}$ do not exist. I therefore draw inference about $\boldsymbol{\alpha}_t$ using a sequence of four steps: (i) Kalman (1960) filter; (ii) Fixed Interval Kalman Smoother (FIKS) due to de Jong (1989); (iii) Quasi Maximum Likelihood (QML) à *la* Durbin and Koopman (2012) and Shumway and Stoffer (2016) among others; and (iv) Parametric Bootstrapping (PB) as in Rodriguez and Ruiz (2009).[1] The full description of technical details related to the estimation of the SS model are presented in the online appendix Sections B, C, and D. Furthermore, the online appendix E provides an accompanying non-technical summary of how I implement each step of the SS model estimation algorithm. In addition, I study the robustness of my inference to potential model misspecification due to: (i) mutually correlated disturbances $\mathbf{u}_t$ and ε_t; and (ii) Autoregressive Conditional Heteroscedasticity (ARCH), the technical details of which are subsumed in the aforementioned sections of the online appendix. Finally, I compare the shock-dependent estimates of pass-through predicted by the SVAR with those of the ARDL in online appendix F. I find no evidence of simultaneity bias mentioned in Section 2.

4. Data

Table 1 provides the description of the data used to estimate the ARDL and the SS models. My goal is to estimate ERPT into the aggregate multilateral U.S. terms of trade. However, I use two different measures of aggregate import and export prices: (i) TXT excludes primary commodities; and (ii) TOT includes all prices (i.e. manufactured goods, services, and commodities). Moreover, I estimate ERPT for the terms of trade as a whole as well as import and export prices separately. This identifies how important is the positive covariance between import and export prices for estimates of ERPT into the terms of trade. That is why there are six entries for the measurement (i.e. dependent) variable in Table 1. Given the focus on multilateral

[1] There exist other more computationally-efficient Bayesian methods of estimating σ and Ξ, such as the Gibbs Sampling (GS) method as in Kim and Nelson (1999) and the Simulation Smoother (SIMS) due to de Jong and Shephard (1995). But GS and SIMS are arguably less intuitive than QML, FIKS, and PB, thus conceptually less comparable to the OLS estimates, and in some cases subject to prior misspecification.

Table 1
Data description (1990:Q1–2018:Q4).

Variable	Abbreviation	Description	Details
Exchange Rate e_t	NEER	Nominal Effective Exchange Rate	Log USD Price of Foreign Currency
Measurement Variable y_t	MXD	Effective Non-Commodity Import Price	Seasonally-Adjusted Log Price Index (USD)
	MTD	Effective Total Import Price	Seasonally-Adjusted Log Price Index (USD)
	XXD	Effective Non-Commodity Export Price	Seasonally-Adjusted Log Price Index (USD)
	XTD	Effective Total Export Price	Seasonally-Adjusted Log Price Index (USD)
	TXT	Non-Commodity Terms of Trade	= MXD–XXD
	TOT	Total Terms of Trade	= MTD–XTD
Confounding Factors $\mathbf{z}_t$	XTC	Competitor Export Price	Seasonally-Adjusted Log Price Index (Foreign Currency Units)
	ULC	Unit Labour Costs	Seasonally-Adjusted Log Price Index (USD)
	GDP	Gross Domestic Product	Seasonally-Adjusted Log GDP at Constant Prices (USD)
Observable Factors $\mathbf{s}_t$	GAP	Output Gap	One-Sided HP Filtered Cyclical Component of GDP (Percent)
	CMS	Commodity Import Share	Primary Commodity Import Share of Total Imports (Percent)
	IPR	Import Penetration Ratio	Total Import Share of Domestic Absorption (Percent)
	DVXM	Domestic Value-Added in Imports	Interpolated Total Re-imports (Percent)
	FVAX	Foreign Value-Added in Exports	Interpolated Total Intermediate Imports (Percent)
	VIX	Market Uncertainty	Log Index of Expected Stock Market Volatility
	NIR	Quarterly Nominal Interest Rate	3-Month Treasury Bill (Percent)
	TIHP	Trend Inflation	One-Sided HP Filtered Trend Component of CPI Inflation (Percent)
	ΔNEER	Direction of Nominal Effective Exchange Rate Changes	Log First-Differenced NEER (Percent)
	|ΔNEER|	Size of Nominal Effective Exchange Rate Changes	Absolute Value of Log First-Differenced NEER (Percent)

Source: OECD Economic Outlook, OECD Quarterly National Accounts, IMF International Financial Statistics, FED, and UNCTAD-Eora. Seasonal adjustment uses the U.S. Census Bureau's X-13ARIMA-SEATS method. One-sided Hodrick-Prescott filter follows the formulation of Meyer-Gohde (2010) with a standard quarterly smoothing factor value of 1600. A more detailed description of the data and the time series plots are provided in the annex to the online appendix H.

terms of trade in this paper, I estimate ERPT using the fluctuations in the broad value of the U.S. dollar (NEER). This measure is arguably the most consistent with the multilateral import and export price data as they are all constructed from chain-linked trade-weighted averages of bilateral time series data. I introduce three relatively standard confounding factors that simultaneously capture the domestic and foreign demand-pull and cost-push pressures as well as strategic complementarities. In particular, domestic GDP represents a demand shifter, domestic unit labour costs (ULC) are a domestic cost-push factor, and the competitor export price index (XTC) captures other external factors, such as foreign cost-push shocks and foreign mark-up shocks, that affect both domestic import and export prices. Finally, I study if the time variation of pass-through can be explained by other observable factors, such as the overall U.S. trade openness proxied by the import penetration ratio (IPR), measures of value-added in U.S. imports and exports (DVXM and FVAX), index of market uncertainty (VIX), the FED policy rate (NIR), the U.S. trend inflation (TIHP), and the direction as well as the size of the broad U.S. dollar movements.

5. Results

The empirical results are split into three different sections. I first present the ARDL estimates of the average (i.e. time-invariant) pass-though into the U.S. terms of trade. Second, I show the simplest SS model estimates of time-varying pass-through into the U.S. terms of trade under the assumption that all latent state variables (incl. ERPT) are random walk processes. Third, I study whether the SS model estimates of time-varying pass-through are robust to richer model specifications and whether its time variation can be explained by any observable factors, including structural breaks in these observable factors.

5.1. Time-invariant ERPT

Table 2 presents the OLS estimates of time-invariant ERPT using the simple ARDL model depicted in Eq. (1), where the dependent variable is the non-commodity terms of trade (TXT) or the total terms of trade (TOT). For completeness, Table 2 also shows analogous estimates of ERPT into import and export prices. This illustrates whether and how their covariance affects the estimates of the time-invariant ERPT into the terms of trade. To reiterate, coefficient ϕ measures the short-run ERPT, π measures the long-run ERPT, and λ measures the rate at which ϕ converges to π. If either ϕ or π are in the vicinity of zero, then the terms of trade are said to be on average "neutral". And when the magnitudes of coefficients ϕ and π resem-

Table 2
OLS estimates of ERPT into the U.S. terms of trade.

	Terms of Trade		*Import Prices*		*Export Prices*	
	Non-Commodity TXT	*Total* TOT	*Non-Commodity* MXD	*Total* MTD	*Non-Commodity* XXD	*Total* XTD
ϕ	0.15 (0.03)	0.31 (0.04)	0.25 (0.06)	0.59 (0.06)	0.08 (0.02)	0.29 (0.02)
π	0.15 (0.03)	0.33 (0.04)	0.25 (0.06)	0.73 (0.08)	0.12 (0.03)	0.40 (0.03)
λ	-0.02 (0.08)	0.09 (0.07)	-0.01 (0.08)	0.18 (0.07)	0.31 (0.09)	0.28 (0.04)
R^2	0.36	0.49	0.32	0.70	0.18	0.70
Ljung-Box	0.50	0.66	0.18	0.79	0.86	0.30
Engle	0.00	0.60	0.33	0.39	0.12	0.09

The table displays OLS coefficient estimates of a simple ARDL model described in Eq. (1) in which $p = 0$, such that we have $\Delta\tau_t = \lambda\Delta\tau_{t-1} + \phi\Delta e_t + \mathbf{z}_t\zeta + \varepsilon_t$. The numbers in parentheses denote the *Newey-West* standard errors (i.e. HAC robust). Coefficient ϕ measures the short-run ERPT, π measures the long-run ERPT, and λ measures the rate at which ϕ converges to π. The standard error of coefficient $\pi = \phi/(1-\lambda)$ is bootstrapped using a large number of replications. The rows labelled *Ljung-Box* and *Engle* display the p-values of standard diagnostic test statistics for the null hypothesis of no serial correlation and homoscedasticity, respectively. The vector of confounding factors consists of $\mathbf{z} = [\Delta\text{XTC}, \Delta\text{ULC}, \Delta\text{GDP}]$ for the terms of trade, $\mathbf{z} = [\Delta\text{XTC}, \Delta\text{GDP}]$ for the import prices, and $\mathbf{z} = [\Delta\text{XTC}, \Delta\text{ULC}]$ for the export prices (see Table 1 for variable descriptions).

ble one another closely, ERPT is said to be *immediate*, in which case the time horizon h and the coefficient π are practically irrelevant.

The key results presented in Table 2 are summarised as follows. First, as expected, ERPT into TXT is low (15%), which is around one-half of the ERPT into TOT (31%). Second, the estimates of ERPT into the terms of trade are remarkably precise, such that the *Newey-West* standard errors are only 3% (4%) for the TXT (TOT). Third, ERPT into either measure of the terms of trade is almost immediate, such that there is no discernible difference between coefficients ϕ and π and, statistically speaking, time horizon h is irrelevant (i.e. λ is not significantly different from zero). Fourth, the rudimentary ARDL model in which $p = 0$ explains around one-third (one-half) of the variation in TXT (TOT) (see row labelled as R^2 in Table 2), but the goodness of fit improves with higher values of p (not displayed). Fifth, no serial correlation is detected even for the most primitive ARDL model specification in which $p = 0$ (see row labelled as *Ljung-Box* in Table 2), but unlike TOT, TXT is subject to autoregressive conditional heteroscedasticity (see row labelled as *Engle* in Table 2).

These results show that the non-commodity terms of trade are much less responsive to the U.S. dollar fluctuations than the total terms of trade, which include all prices (i.e. manufactured goods, services, and primary commodities). Given that the bulk of the U.S. imports and exports are invoiced in U.S. dollar terms (Gopinath (2015)), one would expect that the U.S. terms of trade are orthogonal to the U.S. dollar fluctuations. However, Table 2 shows that both the non-commodity terms of trade and the total terms of trade exhibit a statistically significant response to the U.S. dollar movements. Taken at face value, this result suggests that the observable shares of invoicing currency are informative in a sense that they provide a ballpark magnitude of pass-through for non-commodity prices. But I show that invoicing shares are not always perfect proxies for aggregate exchange rate pass-through, not even in the U.S., because import and export prices are not always nominally rigid in their invoiced currency, especially the prices of primary commodities.

A number of other stylised facts about the magnitude of ERPT into import and export prices displayed in Table 2 are consistent with the existing literature. Most importantly, unlike TXT and TOT as a whole, the time horizon h does seem to matter for MTD and XTD individually, but less so for non-commodity based measures of MXD and XXD. Movements in the U.S. dollar may therefore take some time to be fully reflected in the commodity import and export prices. In particular, similar to Campa and Goldberg (2005), MXD exhibits lower ERPT in both the short-run and the long-run than MTD, since MTD also incorporates raw materials and energy products (see Table 3 in Campa and Goldberg (2005) on p. 684). The same is unambiguously true for XXD and XTD. Consistent with Burstein and Gopinath (2014) among numerous others, I find that short-run ERPT into import prices is significantly lower than the long-run ERPT, but both the short-run and the long-run ERPT are generally *incomplete* (i.e. bounded between zero and unity). Once again, this finding also applies to export prices, but it is much stronger for total import and export prices. And finally, analogously to Choudhri and Hakura (2015), both the short-run and the long-run ERPT is significantly larger for import prices than export prices. Table 2 also shows that this finding generalises to both total and non-commodity import and export prices.

To what extent does the time horizon h matter if we allow for a higher lag order $p > 0$? After all, if the short-run and long-run ERPT into import prices (or export prices) are significantly different, then how robust is the previous finding that the terms of trade as a whole respond to the U.S. dollar movements immediately? Fig. 2 shows the OLS estimates of short-run ERPT ϕ and long-run ERPT π in the context of a higher-order ARDL model specification. First, notice that the choice of the lag order p matters when short-run and long-run ERPT are increasing or decreasing in p. Yet Fig. 2 shows that they are virtually independent of p. Second, the choice of the time horizon h matters when the short-run and long-run ERPT do not coincide (e.g. either $\phi < \pi$ if $\lambda \in (0, 1)$ or $\phi > \pi$ if $\lambda \in [-1, 0)$). However, Fig. 2 shows that both ϕ and π schedules essentially overlap, such that the choice of the time horizon h does not matter even if we allow for the higher lag order $p > 0$. This result applies to both TXT and TOT. However, notice that even if $p > 0$, the short-run and long-run ERPT is still significantly higher for TOT than for TXT. Consequently, the implication that the U.S. terms of trade on average respond to the

Table 3
Determinants of time-varying ERPT.

	(1) Constant			(2) Persistence			(3) Factor Loading		
		$\boldsymbol{\eta}$			$\boldsymbol{\gamma}$			$\boldsymbol{\delta}$	
	TOT	MTD	XTD	TOT	MTD	XTD	TOT	MTD	XTD
AR(1)	0.03*	0.00	0.05***	0.90***	1.00***	0.76***			
	(0.02)	(0.00)	(0.02)	(0.06)	(0.00)	(0.09)			
GAP	0.10***	0.02***	0.07	0.70***	0.98***	0.64	−**4.92*****	−**0.86*****	−**1.19*****
	(0.04)	(0.003)	(0.03)	(0.104)	(0.003)	(0.14)	(0.05)	(0.07)	(0.04)
CMS	0.06***	0.07***	0.04***	0.82	0.93***	0.81	−0.22	−0.16	0.08
	(0.01)	(0.002)	(0.001)	(0.02)	(0.002)	(0.01)	(0.34)	(0.107)	(0.12)
IPR	0.06***	0.18***	0.06***	0.81***	0.83***	0.72***	−0.41	−**0.82*****	0.08
	(0.01)	(0.023)	(0.005)	(0.03)	(0.022)	(0.02)	(0.31)	(0.21)	(0.11)
DVXM	0.06***	0.11***		0.82***	0.9***		−0.16	−0.14	
	(0.004)	(0.002)		(0.01)	(0.002)		(0.29)	(0.11)	
FVAX	0.06***		0.06***	0.82***		0.71***	−0.21		0.15
	(0.01)		(0.01)	(0.02)		(0.03)	(0.329)		(0.17)
VIX	0.06***	0.07***	0.06***	0.84	0.93***	0.73***	−0.26	−**0.22***	0.07
	(0.01)	(0.002)	(0.003)	(0.023)	(0.002)	(0.01)	(0.33)	(0.13)	(0.13)
NIR	0.06***	0.04***	0.09***	0.84***	0.97***	0.57***	−**0.58*****	−**0.58*****	−**0.80*****
	(0.01)	(0.002)	(0.003)	(0.03)	(0.002)	(0.01)	(0.04)	(0.07)	(0.02)
TIHP	0.04***	0.05***	0.07***	0.88***	0.95***	0.68***	−**2.12*****	−**4.37*****	−**1.28*****
	(0.02)	(0.01)	(0.01)	(0.05)	(0.01)	(0.03)	(0.04)	(0.04)	(0.01)
ΔNEER	0.06***	0.01***	0.04***	0.82***	0.99***	0.82***	−0.08	0.01	0.01
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.57)	(0.01)	(0.04)
|ΔNEER|	0.06***	0.19***	0.04***	0.81***	0.81***	0.81***	−0.03	−0.02***	0.01
	(0.00)	(0.00)	(0.00)	(0.001)	(0.00)	(0.00)	(0.09)	(0.03)	(0.05)

The table shows the parameter estimates in the state transition Eq. (3) for the latent variable ϕ_t, which measures the short-run time-varying ERPT and is an element of the unobserved state vector $\boldsymbol{\alpha}_t$. The numbers displayed in the parentheses are the bootstrapped standard errors. The bold numbers marks statistically significant factor loadings. The number of asterisks next to the estimates, namely *, **, or ***, indicate the 10%, 5%, and 1% level of statistical significance.

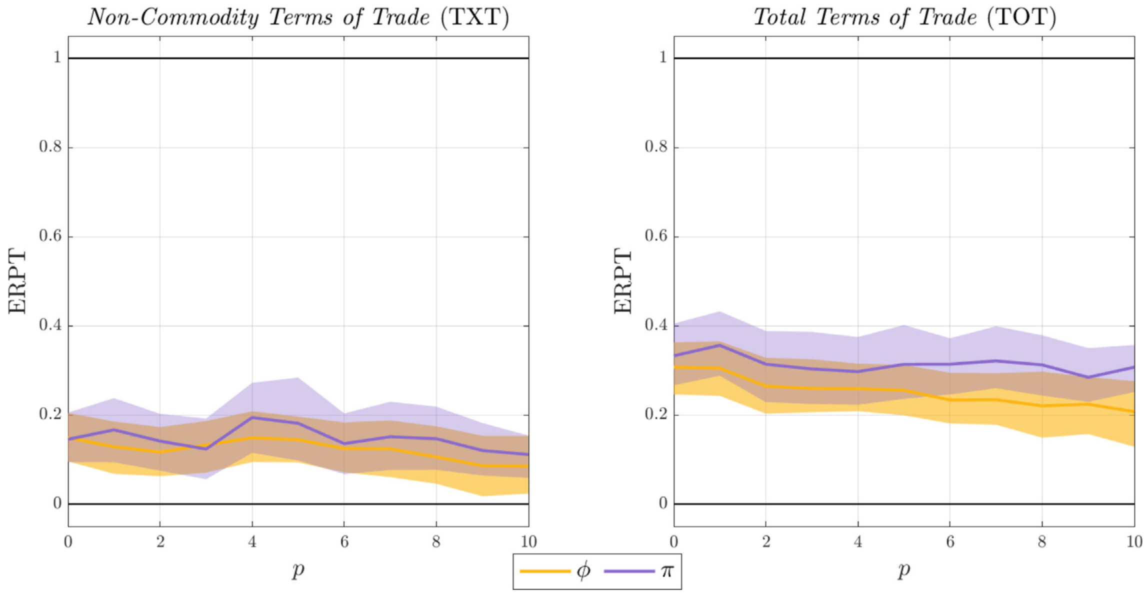

Fig. 2. OLS Estimates of ERPT into U.S. Terms of Trade – Does h and p Matter?. The figure displays OLS coefficient estimates of a p-th order ARDL model depicted in Eq. (1). The solid lines (shaded areas) are the bootstrapped median value of the coefficient estimates (95% confidence intervals). The coefficient ϕ measures the short-run ERPT, whereas π measures the long-run ERPT. The vector of confounding factors consists of $\mathbf{z} = [\Delta\text{XTC}, \Delta\text{ULC}, \Delta\text{GDP}]$ (see Table 1 for variable descriptions).

U.S. dollar fluctuations immediately (i.e. within a quarter) seems robust to potential model misspecification due to the pseudo-arbitrary choice of the lag order p or time horizon h.

Based on these findings, I henceforth focus on the most parsimonious SS model specifications in which $p = 0$. This modelling assumption is further motivated by the fact that I do not detect serial correlation of the residuals even if I choose the lag order p to be equal to zero (see row labelled as *Ljung-Box* in Table 2). Moreover, as explained in Section 3.2, I model the time variation of ERPT into the terms of trade using a state-space approach, which is subject to the "curse of dimensionality". Consequently, setting a higher lag order p comes at a cost of a greater computational burden. But given that I show that ERPT into the terms of trade is on average independent of p, I lose virtually no flexibility or robustness if I chose lag order p that is close to or equal to zero.[2]

5.2. Time-varying ERPT

5.2.1. Baseline: random walk estimates

Fig. 3 presents the time-varying estimates of ERPT into the terms of trade using the SS model described in Section 3.2. In generating these results, I assume that all latent state variables $\boldsymbol{\alpha}_t$ follow a random walk, such that the state-transition Eq. (3) simplifies to $\boldsymbol{\alpha}_t = \boldsymbol{\alpha}_{t-1} + \mathbf{u}_t$. Using the random walk specification of the state-transition equation allows the data to "speak for itself" in terms of how much time variation of pass-through, if any, there is, because it involves the fewest number of parametric restrictions on the transitional dynamics. Fig. 3 shows that these estimates of ERPT into the total terms of trade are remarkably time-varying. Specifically, it decreases from 60% in 1990 to 15% in 2003, then rises back to 60% in 2008, and gradually reverts to 10% in 2015. By contrast, ERPT into the non-commodity terms of trade is virtually time-invariant and equals around 15% throughout the entire sample, which is similar to the time-invariant estimates (see Table 2).

These results are surprising, because Gopinath and Rigobon (2008) show that over 90% (97%) of all U.S. imports (exports) over the period of 1994–2005 were invoiced in U.S. dollars. Moreover, the annual changes in the share of U.S. imports invoiced in U.S. dollars over the period of 1995–2014 are negligible (see Gopinath (2015) fig. 5 on p. 13). This means that over the past few decades, the U.S. paid for most of its imports and sold most of its exports to the rest of the world in U.S. dollar terms. If all global prices were then sticky in U.S. dollars in the short-run as suggested by the DCP proponents (Gopinath et al. (2020)), then U.S. dollar fluctuations would have a negligible effect on the U.S. import and export prices. In particular, if we take the invoicing shares at face value, then an exogenous U.S. dollar depreciation would cause total import (export) prices to increase by 10% (3%), such that the exchange rate pass-through into the U.S. terms of trade would be around 7%. This prediction turns out to be broadly consistent with the estimates of pass-through into the non-commodity

[2] Fig. 4 verifies this statement in which I present the SS model estimates of ERPT with $p = 0, p = 1$, and $p = 2$, all of which give statistically indistinguishable ERPT estimates).

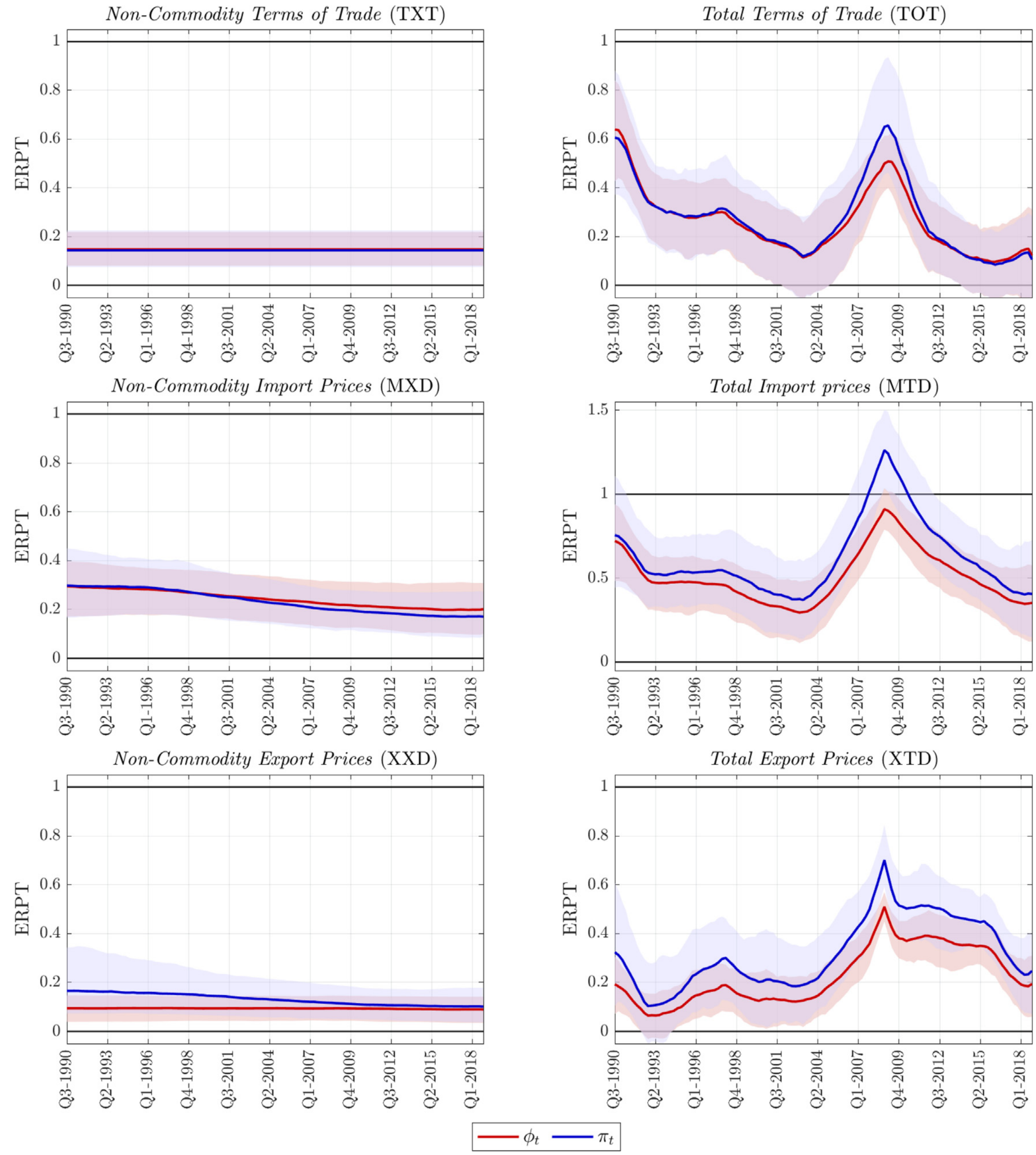

Fig. 3. Time-Varying ERPT into U.S. Terms of Trade (State-Space Model). The figure displays the SS model estimates of the time-varying exchange rate pass-through (ERPT) depicted in Eqs. (2) and (3), where $p = 0$, consistent with OLS results in Table 2. The solid lines denote the median value of the time-varying ERPT at a point in time indicated on the horizontal axis, while the shaded areas represent the bootstrapped 95% confidence intervals. The coefficient ϕ_t measures the short-run ERPT, whereas π_t measures the long-run ERPT. The vector of confounding factors consists of $\mathbf{z} = [\Delta XTC, \Delta ULC, \Delta GDP]$ for the terms of trade, $\mathbf{z} = [\Delta XTC, \Delta GDP]$ for the import prices, and $\mathbf{z} = [\Delta XTC, \Delta ULC]$ for the export prices (see Table 1 for variable descriptions).

terms of trade, since non-commodity import and export prices are notoriously invoiced and sticky in U.S. dollars (Boz et al. (2017)). However, the relatively stable and large U.S. dollar invoicing shares are inconsistent with the time variation of pass-through into the total terms of trade that I estimate.

The discrepancy between the time variation of pass-through and the relatively stable invoicing patterns can be reconciled by the dynamics of commodity prices. In particular, I find that the pass-through into the terms of trade is time-varying only if the terms of trade include commodity prices, otherwise the pass-through is time-invariant. If so, then there are two explanations for why commodity prices play such an important role for pass-through. First, commodity import and export prices may be invoiced, but not always sticky in U.S. dollar terms, unlike the prices of manufactured goods and services (i.e. noncommdities). This argument is further supported by the micro data-based estimates of the relatively high average frequency of commodity price adjustment documented by Bils and Klenow (2004). Second, the commodity share of imports and exports may themselves be time-varying even if pass-through into commodity prices is not. Time variation of pass-through into aggregate terms of trade may therefore reflect changes in the composition of U.S. imports and exports rather than changes in the actual pass-through into commodity prices.

5.2.2. Generalised state-space model

I now study whether the baseline results are robust to the alternative SS model specifications that accommodate richer dynamics. Fig. 4 presents the analogous estimates of exchange rate pass-through into the total and non-commodity terms of trade, but with several alternative model specifications. For now, none of these additional model specifications incorporate any of the observable factors $\mathbf{s}_t$, the role of which is discussed in Section 5.3. In particular, (i) SS(0) is the identical baseline model specification to that in Fig. 3; (ii) SS(1) and SS(2) specifications are exactly the same as the baseline SS(0), except these specifications extend the ARDL lag order to $p = 1$ and $p = 2$, respectively; (iii) the SS(0)-AR(1) specification introduces a state-transition equation with an autoregressive coefficient matrix $\boldsymbol{\gamma}$, each element of which are estimated freely on an interval between -1 and 1 and may not coincide with the explicitly imposed unit roots by the SS(0) model; (iv) the SS(0)-CORR specification allows for the mutual correlation of disturbances in the measurement equation and the state-transition equation (i.e. correlation between unexplained changes in the terms of trade and pass-through); and (v) SS(0)-ARCH admits autoregressive conditional heteroscedasticity for the measurement variable (i.e. terms of trade volatility clustering).

I find that the baseline SS model predictions are robust to virtually all of the model extensions considered in this paper. Specifically, all of the SS model extensions predict that pass-through into the total terms of trade remains significantly different from zero and unity throughout the sample. It also reaches an all-time low during the 2001–03 period and all-time high in 1990 and again 2009, analogous to the baseline SS model predictions. Notice that increasing the lag order p does not generate significantly different estimates of time-varying pass-through into the total terms of trade. At the same time, pass-though into the non-commodity terms of trade starts to somewhat vary over time with either a higher lag order or a stationary law of motion for pass-through. However, if anything, pass-through into the non-commodity terms of trade is decreasing incrementally over time in line with the slight and gradual rise in the share of U.S. imports invoiced in U.S. dollars during the sample (see Gopinath (2015) fig. 5 on p. 13). Therefore, the time variation of pass-through between the total terms of trade and the non-commodity terms of trade remains significantly different and for all intents and purposes similar to the baseline estimates.

5.2.3. Alternative estimates: rolling window regression

For the sake of robustness, I also estimate time-varying ERPT using a rolling-window (RW) regression approach.[3] Fig. 4 presents two different estimates titled RW(20) and RW(40), which refer to two different rolling-window regression specifications, where the length of the window is set to 20 quarters (i.e. 5 years) and 40 quarters (i.e. 10 years), respectively. First, notice that RW(20) predict the most time variation of pass-through out of all model specifications considered in this paper. Second, the RW(20) and RW(40) estimates resemble one another poorly, which means that the results are sensitive to the chosen length of the window. Specifically, if the window is relatively long (e.g. 40 quarters), then unsurprisingly RW(40) predicts virtually none of the time variation of pass-through that occurs at the business cycle frequency. Conversely, if the window is relatively short (e.g. 20 quarters), then RW(20) predicts "delayed overshooting". Namely, pass-through peaks years after and to a much greater extent compared to the state-space model estimates. Moreover, by construction, the RW approach infers the time variation of pass-through without simultaneously projecting it onto any observable factors. I therefore conclude that the RW approach is not well-suited to infer either "how much" or "why" pass-through varies over time.

5.3. What drives time-varying pass-through into terms of trade?

Fig. 5 presents the estimates of time-varying ERPT into the aggregate U.S. terms of trade (TOT) conditional on observable factors as shown in Eqs. (2) and (3). Unlike unconditional estimates of ERPT discussed in Section 5.2, which infer the overall time variation of pass-through, the conditional estimates of ERPT discussed below offer an answer to not only the question as to "how much" pass-through varies over time, but also "why". Because ERPT is unobservable, the standard measures for the goodness of fit do not exist. Consequently, I refer to the observable factors as determinants of ERPT if and only if the factor loadings $\boldsymbol{\delta}$ entering the state transition Eq. (3) are statistically significant. Table 3 therefore presents the estimated parameters in the state transition equation.

One concern about the results presented in Table 3 is that the effect of the observable factors on the time-varying ERPT into TOT could in principal be obscured by relatively stable dynamics of the observable factors. Instead, large outlier observations (i.e. structural breaks) in observable factors could be the underlying source of the time variation of ERPT into TOT. To address this concern, Table 4 presents analogous parameter estimates to those in Table 3, but this time the state transition

[3] The RW approach estimates $\boldsymbol{\alpha}_t$ in closed form by dissecting the entire sample T into finite number of subsamples of size w (i.e. windows). The RW estimator of $\boldsymbol{\alpha}_t$ then stacks the OLS estimates of each individual element of $\boldsymbol{\alpha}_t$ that span w number of time periods (e.g. from $t = 1$ to $t = 1 + w$, then from $t = 2$ to $t = 2 + w$, etc. until $t = T - w$ to $t = T$), which ultimately amounts to a time series $\hat{\boldsymbol{\alpha}}_t$ of size $T - w$ (e.g. Choudhri and Hakura (2006),Cunningham et al. (2017), Jašová et al. (2019),Lilley et al. (2019)).

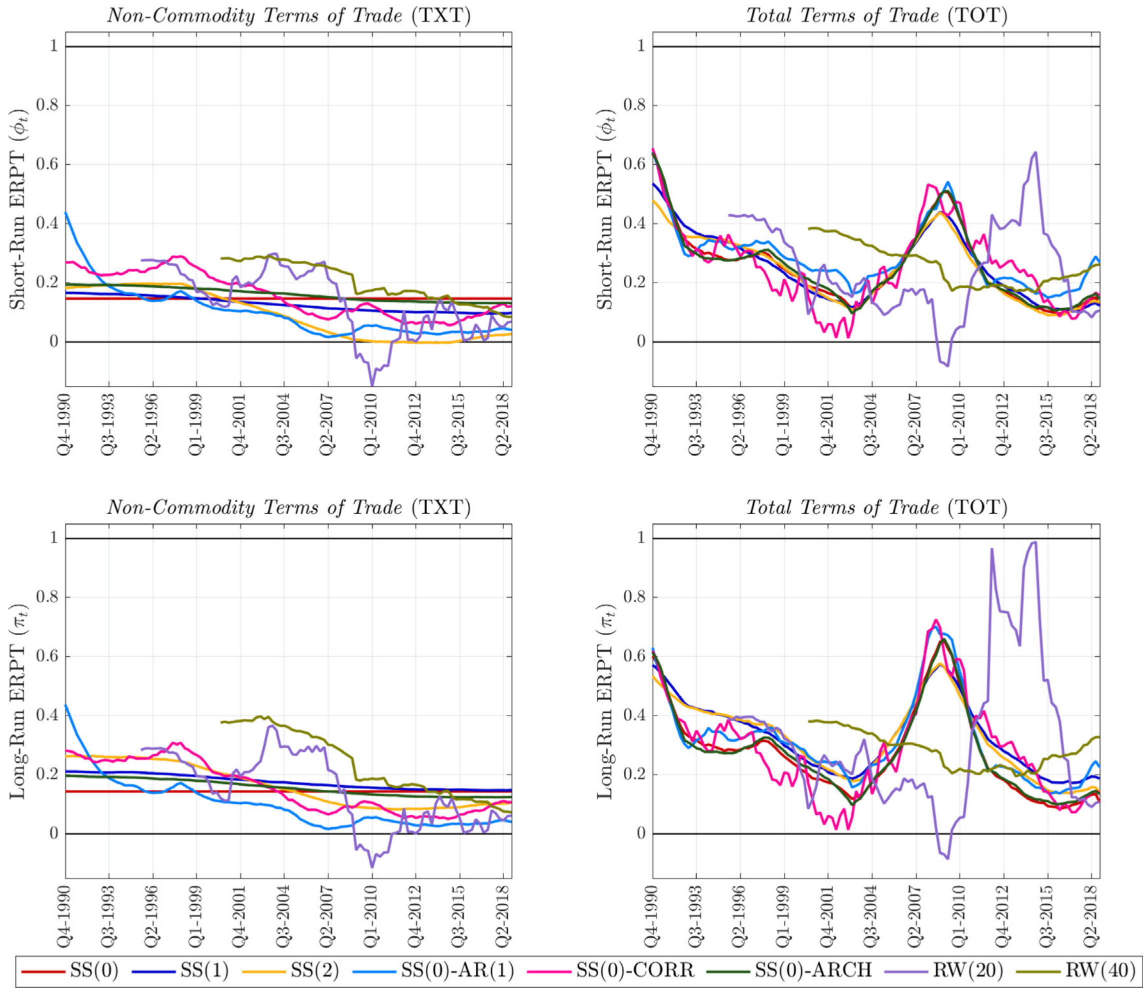

Fig. 4. Time-Varying ERPT into U.S. Terms of Trade (Generalised State-Space Model and Rolling Window Regressions). The four subplots in this figure display the state-space model estimates of time-varying exchange rate pass-through (ERPT) depicted in Eqs. (2) and (3) as well as analogous estimates using the rolling-window approach (i.e. RW(20) and RW(40)). The coloured lines denote the median value of the time-varying ERPT into terms of trade at a point in time indicated on the horizontal axis. The coefficient ϕ_t measures the short-run ERPT, whereas π_t measures the long-run ERPT. The vector of confounding factors consists of $\mathbf{z} = [\Delta XTC, \Delta ULC, \Delta GDP]$ for the terms of trade, $\mathbf{z} = [\Delta XTC, \Delta GDP]$ for the import prices, and $\mathbf{z} = [\Delta XTC, \Delta ULC]$ for the export prices (see Table 1 for variable descriptions).

equation incorporates not only one single observable factor, but also a corresponding structural break component as an additional regressor (i.e. "slope shifter"). I identify structural breaks in observable factors as time periods in which their growth rate exceeds 1.5 standard deviations.

5.3.1. Output Gap (GAP)

I find that the state of the U.S. business cycle measured by the output gap (GAP) is the most economically and statistically significant determinant of ERPT time variation. The estimated factor loading is -4.92 with negligible parameter uncertainty surrounding the estimate (see column (3) in Table 3). This implies that a 1% increase in the output gap leads to around 5% lower exchange rate pass-through into the U.S. terms of trade (i.e. counter-cyclicality). Allowing for structural breaks generates an even greater negative factor loading of -7.12 with a slope shifter value of -0.91 (see columns (3) and (4) in Table 4).

Given that GAP fell dramatically from $+1\%$ in 2006 to below -4% in 2009, the SS model estimate of $\boldsymbol{\delta}$ implies that GAP contemporaneously accounts for around 25–40 percentage point increase in the short-run ERPT. Coupled with the fact that ERPT into the non-commodity terms of trade shows virtually no time variation, I conclude that ERPT counter-cyclicality is attributable solely to the primary commodity prices that are more likely to be sticky in U.S. dollars during expansions as that is when the U.S. terms of trade exhibit low pass-through. But in recessionary times, primary commodity prices are more likely to be sticky in non-U.S. dollar terms, because pass-through into the U.S. terms of trade increases.

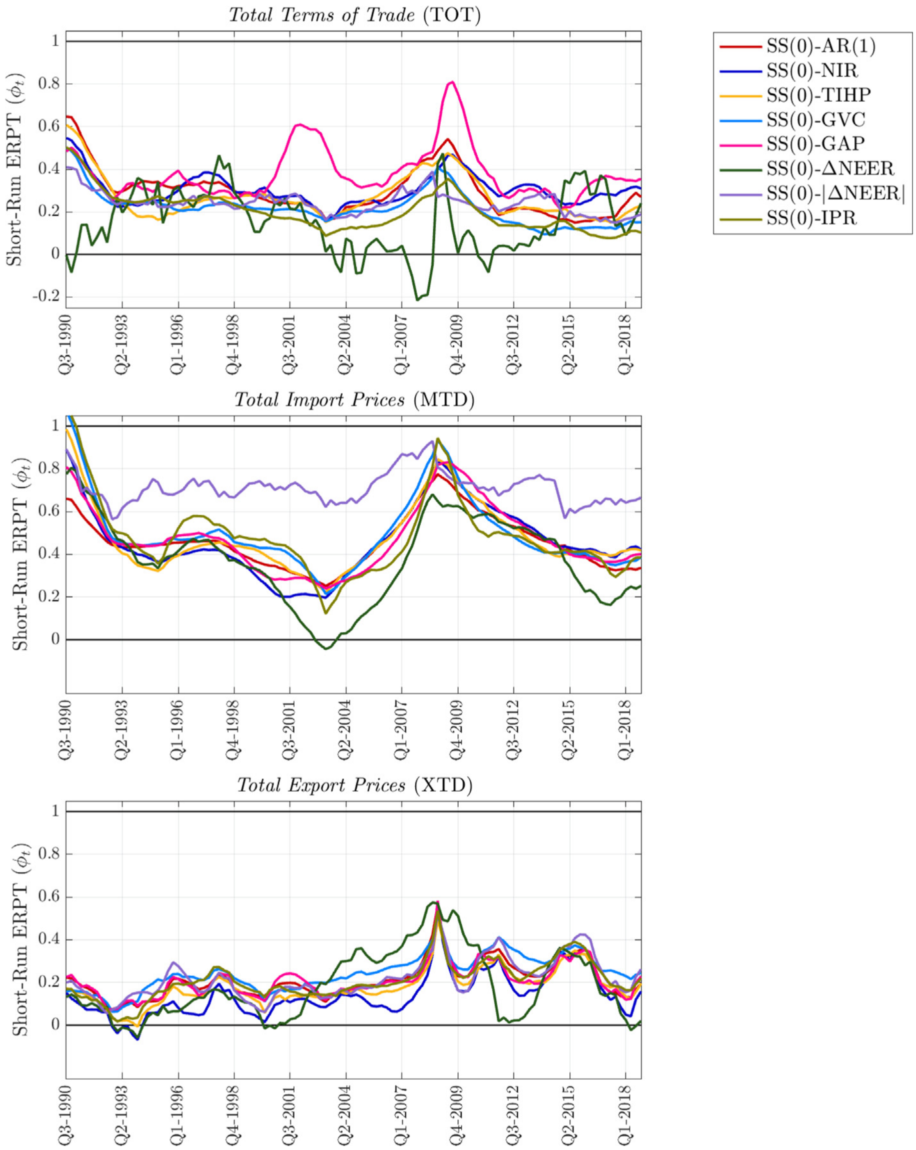

Fig. 5. Conditional time-varying exchange rate pass-through. Each subplot displays the state-space model estimates of the median time-varying ERPT depicted in Eqs. (2) and (3). The vertical axis measures the short-run ERPT measured by coefficient ϕ_t. The vector of confounding factors consists of $\mathbf{z} = [\Delta\text{XTC}, \Delta\text{ULC}, \Delta\text{GDP}]$ for the terms of trade, $\mathbf{z} = [\Delta\text{XTC}, \Delta\text{GDP}]$ for the import prices, and $\mathbf{z} = [\Delta\text{XTC}, \Delta\text{ULC}]$ for the export prices (see Table 1 for variable descriptions). The list of observable factors $\mathbf{s}_t$ are identical to those presented in Tables 1 and 3.

Intuitively, the U.S. is a large open economy and its business cycle spills over into the rest of the world, which is in turn is strongly correlated with the global boom-bust cycles of primary commodity prices. Movements in the U.S. dollar may therefore have less of an effect on primary commodity prices when the world economy is booming and commodity producer profit margins are relative high compared to when the world economy is dwindling.

5.3.2. Commodity share of imports (CMS)

If we assume that all primary commodity export (import) prices are invoiced in U.S. dollars, but sticky in (non-) U.S. dollar terms, otherwise known as Producer Currency Pricing (PCP), then in theory, exchange rate pass-through into the U.S. terms of trade would correspond to the U.S. commodity share of imports (CMS). I find that the factor loading for CMS is not statistically significant (see column (3) in Table 3). However, structural breaks in CMS increase ERPT significantly, such that the slope-shifting factor loading is positive and equal to 0.23 (see columns (3) and (4) in Table 4). While the absolute size of the coefficient is relatively small, the CMS time series increases from around 0.3 in 2006 to nearly 0.5 in 2008 and then goes back to just below 0.3 in 2009. These sharp changes in CMS mostly reflect the steep rise in global oil prices in the run-up

Table 4
Determinants of time-varying ERPT with structural breaks in observable factors.

	(1) Constant			(2) Persistence			(3) Factor Loading			(4) Slope Shifter		
		η			γ			δ			δ_B	
	TOT	MTD	XTD	TOT	MTD	XTD	TOT	MTD	XTD	TOT	MTD	XTD
GAP	0.19^{***}	0.02^{***}	0.10^{**}	0.45^{***}	0.98^{***}	0.51^{***}	$-\mathbf{7.12}^{***}$	$-\mathbf{0.63}^{***}$	$-\mathbf{2.68}^{***}$	$-\mathbf{0.91}^{***}$	$\mathbf{0.65}^{***}$	$\mathbf{0.38}^{***}$
	(0.04)	(0.002)	(0.04)	(0.11)	(0.002)	(0.18)	(0.07)	(0.07)	(0.03)	(0.02)	(0.03)	(0.01)
CMS	0.06^{***}	0.08^{***}	0.06^{***}	0.82^{***}	0.92^{***}	0.69^{***}	-0.24	$-\mathbf{0.19}^{**}$	0.04	$\mathbf{0.23}^{***}$	$\mathbf{0.74}^{***}$	$\mathbf{0.42}^{***}$
	(0.01)	(0.001)	(0.003)	(0.02)	(0.001)	(0.014)	(0.36)	(0.08)	(0.07)	(0.01)	(0.004)	(0.01)
IPR	0.07^{***}	0.20^{***}	0.07^{***}	0.79^{***}	0.80^{***}	0.66^{***}	-0.41	$-\mathbf{0.97}^{***}$	0.17	$\mathbf{0.27}^{***}$	$-\mathbf{0.20}^{***}$	$-\mathbf{0.96}^{***}$
	(0.01)	(0.03)	(0.01)	(0.03)	(0.03)	(0.03)	(0.25)	(0.20)	(0.15)	(0.03)	(0.02)	(0.05)
DVXM	0.07^{***}	0.19^{***}		0.8^{***}	0.82^{***}		-0.18	$-\mathbf{0.26}^{**}$		$\mathbf{0.33}^{***}$	$\mathbf{0.79}^{***}$	
	(0.004)	(0.01)		(0.012)	(0.01)		(0.27)	(0.14)		(0.02)	(0.01)	
FVAX	0.08^{***}		0.07^{***}	0.75^{***}		0.65^{***}	$\mathbf{0.52}^{***}$		-0.02	$-\mathbf{0.03}^{*}$		$\mathbf{1.01}^{***}$
	(0.01)		(0.004)	(0.022)		(0.02)	(0.02)		(0.12)	(0.02)		(0.03)
VIX	0.06^{***}	0.07^{***}	0.07^{***}	0.82^{***}	0.93^{***}	0.65^{***}	-0.33	$-\mathbf{0.32}^{**}$	-0.03	$\mathbf{0.51}^{***}$	$\mathbf{1.45}^{***}$	$\mathbf{0.74}^{***}$
	(0.01)	(0.002)	(0.003)	(0.02)	(0.002)	(0.02)	(0.363)	(0.134)	0.148	(0.06)	0.018	(0.02)

The table shows the parameter estimates in the state transition Eq. (3) for the latent variable ϕ_t, which measures the short-run time-varying ERPT and is an element of the unobserved state vector $\boldsymbol{\alpha}_t$. The numbers displayed in the parentheses are the bootstrapped standard errors. The bold numbers marks statistically significant factor loadings in column (3) as well as the structural break slope shifting coefficients in column (4). The number of asterisks next to the estimates, namely *, **, or ***, indicate the 10%, 5%, and 1% level of statistical significance.

to the Great Recession and their slump thereafter. And they explain around 5 percentage points of the peak increase in ERPT into TOT at the time (see Figs. 3 and 5).

5.3.3. Market uncertainty (VIX)

When firms expect high exchange rate volatility, they are more likely to price their exports in producer currency (PCP) in order to protect their profit margins. I proxy the sentiment related to exchange rate uncertainty using the CBOE volatility index (VIX), which measures the expectations of near-term price changes in the S&P 500. I find that the factor loading for VIX is not statistically significant outside of the structural break episodes (see column (3) in Table 3). However, during structural breaks, VIX has a positive and statistically significant factor loading of 0.51 (see columns (3) and (4) in Table 4). Given that VIX rises from around 0.2 in 2007 to nearly 0.6 in 2008 explains around 20 percentage points of the rise in ERPT into TOT in the run-up to the Great Recession shown in Fig. 5.

5.3.4. Trend inflation (TIHP)

Changes in the trend of aggregate inflation (TIHP) is a well-established determinant ERPT. According to Taylor (2000), lower and more stable rate of trend inflation is associated with a lower pricing power of the firms, which decreases both the frequency and the size of their price adjustments in response to exchange rate movements. An increase (decrease) in TIHP is thus expected to increase (decrease) ERPT into TOT, which is broadly consistent with the empirical results of Choudhri and Hakura (2006). However, I find that the factor loading for TIHP is negative and equal to -2.12 for ERPT into TOT (see column (3) in Table 3). One way to reconcile this discrepancy is the fact that Choudhri and Hakura (2006) focus on the stagflationary period of 1979–2000 during which inflation was driven by supply-side (i.e. oil price) shocks, whereas this paper considers a more recent time period of 1990–2018, where demand-side (i.e. financial) shocks played a more prominent role. Hence, the trend inflation rate in the run-up to the Great Recession was just above 1%, such that its subsequent decline accounts for a negligible amount of time variation of ERPT into TOT.

5.3.5. FED Policy Rate (NIR)

Changes in the monetary policy stance are closely related to the movements in the discount rate of exporters whose intertemporal decision of invoicing and price adjustment determines the time-variation of ERPT. Specifically, in the context of the U.S. dollar dominance as the global trade invoicing currency, increase (decrease) in the U.S. FED policy rate is likely to decrease (increase) the ERPT into the U.S. terms of trade. I find that the factor loading on NIR is negative, equal to -0.58, and statistically significant for ERPT into TOT (see column (3) in Table 3). However, NIR accounts for only around 3 percentage point increase in ERPT into TOT in the run-up to the Great Recession as it decreased by around 5% (i.e. 500 basis points) from 2006 to virtually zero in 2009.

5.3.6. Overall Trade Openness (IPR)

Changes in the overall openness to trade in the context of a floating exchange rate is another determinant of ERPT. Theoretically, an increase in the trade openness causes two counteracting effects on the ERPT into the U.S. terms of trade. On the one hand, greater domestic trade openness implies an increase in international contagion and a greater domestic susceptibility to foreign shocks, which increases ERPT into the U.S. terms of trade. On the other hand, greater domestic trade openness leads to greater integration of multinational firms into the domestic product market, which is associated with increased international competitiveness for the local market shares (i.e. pricing-to-market) and an decrease in ERPT into the U.S. terms of trade (Krugman (1986), Atkeson and Burstein (2008)). The overall domestic openness to trade in this paper is measured by the import penetration ratio (IPR), which is defined as the total U.S. import share (i.e. incl. commodities and non-commodities) of the U.S. domestic absorption (i.e. GDP excl. net exports). I find that IPR is not statistically significant outside of structural break episodes (see column (3) in Table 3). However, during structural breaks, the factor loading is positive, equal to 0.27, and statistically significant (see columns (3) and (4) in Table 4). However, due to the relatively stable dynamics of IPR over time, it once again accounts for very little time variation of ERPT into TOT. In particular, it rises steadily from around 7% in 1990 to around 15% in 2018 with only a short-lived decline of around 2% during the Great Recession. I conclude that IPR may be a more revealing determinant of ERPT when comparing its magnitude across different countries than over time for any given country.

5.3.7. Value-added in imports and exports (DVXM and FVAX)

International trade in intermediate goods and services is closely related to the production costs and profit margins of the exporters and can therefore influence ERPT (see Amiti et al. (2014),De Soyres et al. (2018)). Specifically, if the global export prices are sticky in U.S. dollars, then consistent with DCP, the greater is the share of foreign (domestic) intermediate inputs in domestic (foreign) exports, the higher (lower) is the ERPT into domestic export (import) prices (Gopinath et al. (2020)). I study two different measures of trade in intermediate goods and services, which decomposes the total value of trade flows across different U.S. trade parters into the domestic value-added and foreign value-added. In particular, using the UNCTAD-Eora database (Casella et al. (2019)), I measure: (i) the share of domestic value-added in foreign exports (DVXM); and (ii) the share of foreign value-added in domestic exports (FVAX). As such, DVXM (FVAX) is expected to be negatively (positively) related to the time-varying ERPT into domestic import (export) prices and thus negatively related to ERPT into TOT. However, I find that the factor loadings are not statistically significant outside of the structural break episodes (see column (3) in Table 3). But during structural breaks, in particular during the Great Recession, the factor loadings are positive and statistically significant. However, the time variation in DVXM and FVAX during the Great Recession is strongly correlated with the state of the U.S. business cycle as it precipitates the so-called "Great Trade Collapse" (Alessandria et al. (2010)). As a result, they capture similar causes of the time variation of ERPT into TOT as the state of the U.S. business cycle.

5.3.8. Direction and Size of U.S. Dollar Movements ($\Delta NEER$ and $|\Delta NEER|$)

Exchange rate volatility and exchange rate uncertainty are fundamentally different. The former is *ex-post*, while the latter is *ex-ante*. However, in principal, both can influence the degree of exchange rate pass-through. While small exchange rate adjustments or favourable appreciations of domestic currency may be absorbed by exporter profit margins, large depreciations of exporter currency are more likely to be transmitted into international prices. However, I do not find any empirical support for the hypothesis that the direction or the size of the broad U.S. dollar movements has any effect on ERPT into TOT (see column (3) in Table 3), such that aggregate ERPT appears to be linear, but time-varying.

6. Concluding remarks

For the last few decades, the U.S. paid for nearly all of its imports and sold its exports to the rest of the world using the U.S. dollar. If the U.S. import and export prices were sticky in U.S. dollar terms, then exchange rate pass-through (ERPT) into the U.S. terms of trade (TOT) should be close to zero and stable over time. I test this hypothesis by estimating ERPT into TOT using a state-space model and find that it is overwhelmingly rejected. Specifically, I show that ERPT into TOT decreases from 60% in 1990 to 15% in 2003, then rises back to 60% in 2008 during the peak of the financial crisis, and then gradually reverts to 10% in 2015. I also show that the time variation of ERPT into TOT stems from primary commodities, because without primary commodity prices, the average ERPT roughly halves and the time variation subsides considerably. I argue that time-varying ERPT into TOT can be explained by the changing primary commodity share in U.S. imports and the fact that primary commodity prices are invoiced, but not always "sticky", in U.S. dollar terms. In particular, I find that ERPT into TOT is strongly counter-cyclical, such that U.S. TOT become nearly 5% less sensitive to the broad U.S. dollar movements with every 1% increase in the U.S. output gap. This tends to coincide with sharp movements in the CBOE index of market uncertainty, which contributes to the ERPT time variation. Other factors, such as the FED policy rate, U.S. trend inflation, or the U.S. trade openness in final and intermediate goods are generally less important. All this suggests that despite the overwhelmingly dominant use of the U.S. dollar as the vehicle currency in global trade transactions, primary commodity price dynamics preserve a part of the conventional link between the U.S. dollar, the aggregate U.S. terms of trade, and the U.S. current account that is more commonly known as the Harberger-Laursen-Metzler (HLM) effect. Even if the HLM effect in the U.S. is relatively weak, if it is ignored, it may lead us to falsely conclude that the movements in the U.S. dollar are "neutral" to the U.S. economy.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jimonfin.2023.102905.

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