A Trade and Exchange Rate Competition in East Asia: Appendix for Online Publication

A.1 Measuring the Polarity of Newspaper Articles

Latent Semantic Scaling (LSS) represents a second-generation model for text analysis. Initially, it facilitated the positioning of political party manifestos along a political spectrum from left to right. Laver, Benoit, and Garry (2003) employed expert-coded documents to develop a word scoring model capable of ascertaining the ideological leanings of new texts. Subsequently, Slapin and Proksch (2008) conceptualized ideological orientations as latent Poisson variables to measure party positions and their temporal evolution. However, these initial approaches exhibit inherent constraints. Supervised machine learning algorithms necessitate manually classified training datasets that might align closely with the conceptual frameworks of the researchers but are limited to accurately classifying terms present in these predefined datasets. These datasets frequently become so voluminous that they scarcely offer more efficiency than manual categorization methods. In contrast, unsupervised models such as topic modeling techniques derive classifications solely from the distributional characteristics of the texts, yet often fail to capture dimensions of theoretical significance.

The latest innovations in topic modeling combine the adaptability of unsupervised techniques with the precision of supervised approaches through the incorporation of theoretically pertinent, pre-selected keywords (Eshima, Imai, and Sasaki 2020; Gallagher et al. 2017). A similar approach is used in the approach we implement here. Latent Semantic Scaling (LSS) (Watanabe 2021) merges supervised and unsupervised methodologies to enable user-defined scaling dimensions. In its initial, unsupervised phase, LSS develops a set of word embeddings that delineate the semantic positions of terms within a corpus. These embeddings are vector representations that encapsulate contextual usage data, facilitating the identification of semantically similar terms. The subsequent stage involves assessing the polarity of terms by evaluating their proximity to predefined "seed words." Watanabe recommends the following steps that we undertake to generate our data: (1) generate a list of polarity words that are related to the scaling dimension—in our case, concerns about a strong or weak yen; (2) select the words that have the strongest polarity and smallest ambiguity; (3) fit an LSS model with only one seed word to check if the polarity measure is intuitive; (4) combine the list of seed words; and finally (5) check the validity by manually comparing the polarity against human judgement. The resulting polarity measure is then utilized to scale the documents to measure whether their content favors appreciation or depreciation of the yen. The only difference to the original LSS model is that we take advantage of transformer models for the word embeddings.

A sample of seed word lists is provided in tables A1 and A2. Note that several of these keywords are only informative in their context that is captured by the word embeddings. The full list of seed words is included with our replication code. There is considerable overlap in the terminology, but the Korean texts often refer to a weak Japanese yen in the context of direct competition between firms, while Japanese newspaper articles often talk about a (too) strong yen that affects export competitiveness, or on occasion about the effect of a weak dollar. A common theme in Japan is the outsourcing of production from Japan to cheaper production locations ("hollowing out") but this is less commonly voiced in the Korean financial newspaper.

A.2 Validation of Text Polarity

In this section, we demonstrate our validation of the scaling approach: Does our polarity measure, the independent variable of our analysis, represent industry concerns? After scaling our entire corpus of almost 900,000 articles, we look at a sample of texts with high, low, or neutral polarity, and verify that a human reader understands their content as favoring depreciation, favoring appreciation, or neutral, based on their effects on industry.

The majority of articles that mention the exchange rate—event those that specifically mention a "strong yet"—do not express any industry concerns at all and are thus expected to be neutral in their polarity. An example is the following article excerpt from September 29, 1988, that talks

輸出用工場	export-specialized factory	D - favoring depreciation
輸出採算性	export profitability	D - favoring depreciation
水平分業制	horizontal international specialization	D - favoring depreciation
輸入促進	import promotion	A - favoring appreciation
貿易摩擦緩和	mitigation of trade friction	A - favoring appreciation
資材費	capital goods cost	A - favoring appreciation
不採算輸出	unprofitable exports	D - favoring depreciation
安値輸入品の脅威	threat of low priced imports	D - favoring depreciation
円高地合い	strong yen condition	D - favoring depreciation
際競力を失い	loss in international competitiveness	D - favoring depreciation
輸出停	export stagnation	D - favoring depreciation
需不振	sluggish domestic demand	A - favoring appreciation
円高進行	continued strong yen	D - favoring depreciation
輸出採算の化	worsening export profitability	D - favoring depreciation
円高差益	profit from rise in yen	A - favoring appreciation
産業の空洞化	hollowing out of domestic industry	D - favoring depreciation

Table A1: Japanese seed words

about the effect of the exchange rate, but only in the context of government policy proposals (our own English translation follows):

> テクノポリスは地域経済の自立を目指し、一九八三年度に発足した制度。産・学・住が一体となったまちづくりを支援するため、国が税制、財政面での優遇措置を講じている。これまでに通産省は全国で二十五地域をテクノポリスに指定した。しかし、スタート当時には予期しなかった円高による輸出の落ち込みや、海外への工場流出、リストラクチャリング（企業再構築）など、これまでの産業基盤が揺らいできたため、通産省は地域の将来を見つめ直す新たな構想が必要と判断した。
>
> The technopolis system, launched in 1983, aims to promote regional economic independence. The government supports the integrated development of industry, academia, and residential areas with tax and financial incentives. To date, MITI has designated 25 regions across Japan as technopolises. However, unforeseen challenges such as export declines due to the strong yen, the relocation of factories overseas, and industrial restructuring have shaken the foundation of industries since the program's inception.

원화 강세	strong KRW	D - favoring depreciation
고평가	overvaluation	D - favoring depreciation
경쟁력 약화	weakening competitiveness	D - favoring depreciation
수출채산성	export profitability	D - favoring depreciation
수출단가	export unit cost	D - favoring depreciation
달러 약세	weak USD	D - favoring depreciation
단가인상	increase in unit cost	D - favoring depreciation
가격 경쟁력	price competitiveness	D - favoring depreciation
내수주	domestic demand stocks	A - favoring appreciation
수출 감소세	export reduction trend	D - favoring depreciation
엔저현상	weak JPY phenomenon	D - favoring depreciation
수지 적자	an adverse balance of payments	D - favoring depreciation
인플레이션	inflation	A - favoring appreciation
경쟁력 훼손	damage to competitiveness	D - favoring depreciation
수출회복	export recovery	D - favoring depreciation
내수 방어주	domestic demand defensive stock	A - favoring appreciation

Table A2: Korean seed words

> MITI has concluded that a new vision is needed to reevaluate the future of these regions.

This article has a polarity of 0.16, or weakly favorable to depreciation. A similarly nearly-neutral article from April 15, 2013 (Evening edition) discusses the effect of yen depreciation as a consequence of quantitative easing, but in the absence of mention of industry concerns, is just scaled at 0.0462, or slightly favorable of depreciation. The article also hints that depreciation of the yen is seen as unpopular with Japan's trade partners.

> 黒田 東彦 総裁 就任 後 初めて の 支店 長 会議 を 本店 で 開い た 。 足元 の 景気 に つい て 総裁 は 「 持ち直し に 向かう 動き も みられる 」 と 発言 。 消費者物価 も 「 小幅 の マイナス と なっ て いる が 、 予想 物価 上昇 率 の 上昇 を 示唆 する 指標 が みられる 」 と 語り 、 金融 市場 で インフレ 予想 が 広がり つつ ある と の 認識 を 示し た 。 ただ 、 景況 感 好転 の 起点 と なっ た 円安 に 対する 海外 の 視線 は やや 厳しく なっ て いる 。 金融 政策 運営 の かじ取り は 微妙 だ 。

> The Bank of Japan held its first branch managers' meeting under Governor Haruhiko

Kuroda at its headquarters. Regarding the current state of the economy, the governor stated, "There are signs of recovery." He also commented on consumer prices, saying, "While they remain slightly negative, there are indicators suggesting a rise in inflation expectations," indicating his awareness that inflation expectations are spreading in financial markets. However, he noted that overseas scrutiny of the yen's depreciation, which has been a key driver of improving economic sentiment, has become somewhat more critical, making the steering of monetary policy delicate.

Compare this to an article from August 2, 1993, that directly quotes the concerns of an export industry and is scaled at 0.749, indicating strong support for depreciation:

> 造船業界が値下げを要求してくるなら、こっちも鋼材を薄くして出荷してやろうか」。高炉メーカーの厚板営業部長は息巻く。「円高の影響はお互い様。造船だけが苦しいのではない。値下げなんて無理難題だ」。造船業界は「高い鋼材と円高で、韓国など諸外国とのコスト競争力を失いつつある」と主張。だが、営業部長氏は「コスト削減努力は高炉も必死に進めてきた。円高の責任は高炉にはない。助けを求めるところが違うのではないか」という。高炉業界と違って、造船業界は最近まで受注ラッシュに沸いていただけに「我慢が足りない」と憤っていた。
>
> "If the shipbuilding industry is going to demand price cuts, maybe we should ship thinner steel instead," fumes the head of sales at a blast furnace manufacturer. "The impact of the strong yen affects both sides—it's not just the shipbuilding industry that's struggling. Asking for price cuts is an unreasonable demand." The shipbuilding industry argues that "the high cost of steel, combined with the strong yen, is causing us to lose cost competitiveness against countries like South Korea." The sales manager counters, "Blast furnace manufacturers have been working desperately to cut costs as well. The strong yen is not the fault of the steelmakers. They're seeking help from the wrong place."

An article from March 5, 1987 is scaled at 0.645, reflecting its direct emphasis on industry reactions to the strong yen and the "hollowing out" of Japan's manufacturing base:

> 大隈鉄工所は四日、円高や輸出自主規制に対応するため米国でＮＣ（数値制御）旋盤、ＭＣ（マシニングセンター）の一貫生産を始めると発表した。全額出資の現地生産会社「オークマ マシーン ツールス」を二月五日付ですでに設立、生産拠点として米ボルグワーナー社の石油ポンプ部門の工場をこのほど買収した。今年五月十八日をメドに操業を開始し、三年後にＮＣ旋盤、ＭＣ合わせて月産百台体制にする計画。(...)
>
> 現在、同社はＮＣ旋盤、ＭＣ合わせて米国向けに月百台程度輸出している。円高や今年一月からの対米輸出自主規制などで、今後の販売拡大が難しいことから現地での本格生産を決断した。円高がさらに進めば「現地工場から国内への逆輸入も考える」（大隈武雄社長）という。
>
> On March 4, Ōkuma Corporation announced plans to begin integrated production of NC (numerical control) lathes and machining centers (MCs) in the United States to address the challenges posed by the strong yen and voluntary export restrictions. The company has already established a wholly owned local subsidiary, Ōkuma Machine Tools, as of February 5. It recently acquired a factory from BorgWarner's oil pump division to serve as its production base. Operations are scheduled to begin by May 18 this year, with a goal of achieving a monthly production capacity of 100 units (combined NC lathes and MCs) within three years.(...)
>
> Currently, Ōkuma exports about 100 NC lathes and MCs per month to the U.S. However, with the strong yen and voluntary export restrictions to the U.S. in effect since January, the company anticipates difficulties in expanding sales and has decided to establish full-scale local production. President Takeo Ōkuma stated, "If the yen con-

tinues to strengthen, we may consider re-importing products from the local factory back to Japan.” (...)

An article from June 7, 1988 speaks to the same issue, is scaled at 0.604, strongly favoring depreciation:

> ステンレス 鋼線 の トップ メーカー 、 日本 精線 は タイ に 一 〇 〇 ％ 出資 の 現地 法人 を 設立 、 海外生産 に 乗り出す 。 今月 中 に 工場 建設 に 着手 、 来春 から 操業 を 始める 。 円高 に 対応 し 、 東南 アジア 、 米国 など 輸出 向け 製品 の 生産 を 海外 に シフト する 。 現地 法人 の 名称 は 「 タイ 精線 」 （ 資本 金 二 億 円 ） 。 サムットプラカーン 県 の バンプー 工業 団地 内 に 三 万 四千 平方 メートル の 用地 を 取得 、 今月 中旬 、 第 一 期 工事 に 着手 する 。 (...)
>
> Nippon Seisen, Japan’s leading stainless steel wire manufacturer, is establishing a wholly-owned subsidiary in Thailand to commence overseas production. Construction of the factory will begin this month, with operations set to start next spring. This move is aimed at responding to the strong yen and shifting the production of export-oriented products for markets in Southeast Asia and the United States overseas. (...)

An article from December 17, 1995 on the relocation of production and Panasonic’s struggle with the strong yen is scaled at 0.67, favoring depreciation:

> 松下 電器 産業 は 九六 年度 に 中国 で の アイロン 生産 台数 を 倍増 する 。 日本 で 生産 し て いる 輸出 用 アイロン の 六 割 を 中国 に 移管 し 、 年間 百 二十 万 台 の 生産 体制 を 整える 。 広州 市 に ある 合弁 企業 で 増産 する 。 米国 向け に 日本 国 内 で 生産 し て いる スチーム アイロン の うち 、 低 価格 タイプ を 中心 に 六 〇 ％ に あたる 三十 万 台 を 移す 。 中国 で 生産 する 輸出 用 アイロン は 百 万 台 と 今 年度 実績 の 二 倍 に 拡大 。 中国 国内 向け も 十 万 台 から 二十 万 台 に 増やす 。 松下 電器 は アイロン 事業

で国内トップのシェアを持つが、円高などで輸出が伸び悩み、九五年度売上高は百六十五億円程度にとどまる見通し。

Panasonic (Matsushita Electric Industrial Co.) plans to double its production of irons in China during fiscal 1996. The company will transfer 60% of its export iron production currently carried out in Japan to China, establishing an annual production capacity of 1.2 million units. The increased production will be handled by a joint venture in Guangzhou. Of the steam irons produced in Japan for the U.S. market, 300,000 units, or 60%, primarily lower-priced models, will be shifted to China. As a result, the number of export irons produced in China will double to 1 million units compared to the current fiscal year, while production for the domestic Chinese market will increase from 100,000 units to 200,000 units. Panasonic holds the largest share of the domestic iron market, but exports have stagnated due to the strong yen. As a result, its iron business sales for fiscal 1995 are expected to remain around 16.5 billion yen.

Other articles consider the pros and cons of yen appreciation, leading to a more neutral scaling of 0.321 (August 3, 1993 Evening edition):

ある証券会社の株式部長氏、顧客にどう言って株の購入を勧めるか頭を悩ませる。いつものように各紙朝刊を広げると、「円高差益還元でフランス製ファッション大幅値引き」と銘打った百貨店の広告。ほかにも「英国車がお安くなりました」という外車の広告が目に留まった。株式相場欄をみながら「昨日は円高でハイテク株が軒並み安だったな。これも、今買う投資家には円高還元だと思うんだけどなあ」。

A equities manager at a securities company struggles to figure out how to encourage clients to buy stocks. As usual, he opens the morning papers and spots a department store ad proclaiming, “Big discounts on French fashion thanks to yen appreciation savings.” Another ad for imported cars reads, “British cars now more affordable.”

> While glancing at the stock market column, he reflects, “Yesterday, high-tech stocks fell across the board due to the strong yen. But for investors buying now, this could also be seen as yen appreciation savings, don’t you think?”

Articles that emphasize the benefits of a strong yen for importers are scaled to favor appreciation, like this article from May 15, 1994 with a polarization of -0.567:

> キリン ビール 、 花き の 輸入 販売 拡大 —— スプレー 菊 、 今夏 から 苗 も 。 1994 / 05 / 15 日本 経済 新聞 朝刊 7 ページ 430 文字 [1 ページ 17 KB] キリン ビール は 円高 を 背景 に 花き の 輸入 販売 事業 を 拡大 する 。 スプレー 菊 の 輸入 量 を 昨年 の 三 倍 に 増やす と 同時 に 、 新た に 苗 の 輸入 に 乗り出す 。 効率 的 な 栽培 ノウハウ も 提供 し ながら 低 コスト で の 花き 栽培 を 武器 に 栽培 業 者 ・ 農家 向け に 売り込む 。 輸入 事業 を テコ に 現在 グループ 全体 で 百 五十 億 円 の アグリ バイオ 事業 部門 の 売上高 を 九七 年 を メド に 二百 億 円 に 引き上げる こと を ねらう 。
>
> Kirin Brewery is expanding its imported flower sales business, leveraging the strong yen. The company plans to triple its imports of spray chrysanthemums compared to last year and will also begin importing seedlings. By offering efficient cultivation techniques, Kirin aims to promote low-cost flower production and market its products to growers and farmers. Through its import business, the company seeks to increase its agri-bio division’s total group sales from the current ¥15 billion to ¥20 billion by 1997.

In sum, our polarity scales those articles as most favorable of depreciation if they directly quote industry concerns, followed by those that describe the negative effects of a strong currency on exporters, while articles that talk about the exchange rate in unrelated terms are scaled neutrally. If industries benefit from a strong yen, the polarity is reversed. This variable is approximately normally distributed but has a long right tail, as shown in Figure A1.

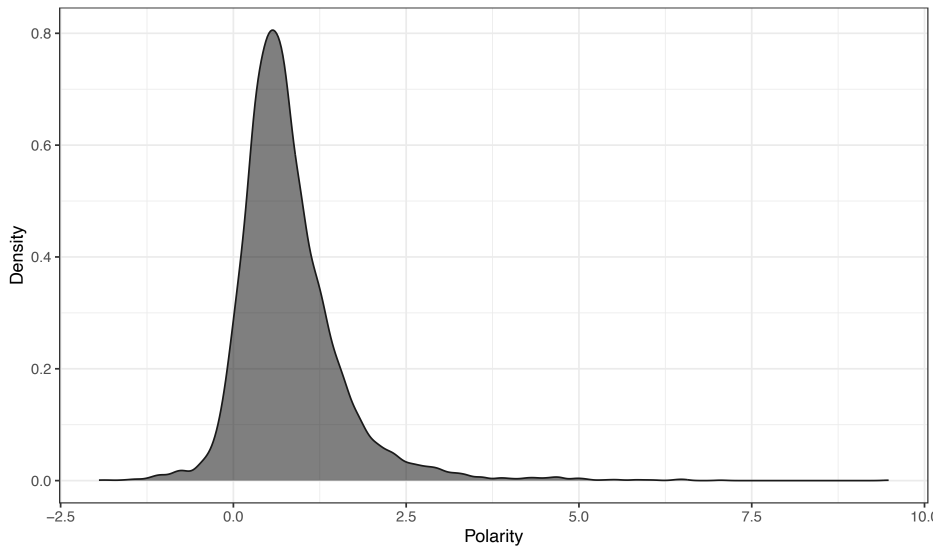


Figure A1: Kernel density estimate of polarity scores in the sample.

A.3 Standard Errors via Delta Method

Figure A2 shows the results from the original models after calculating the error bands with the delta method instead of the block-bootstrapped procedure, yielding narrower bands than those shown in the main paper.

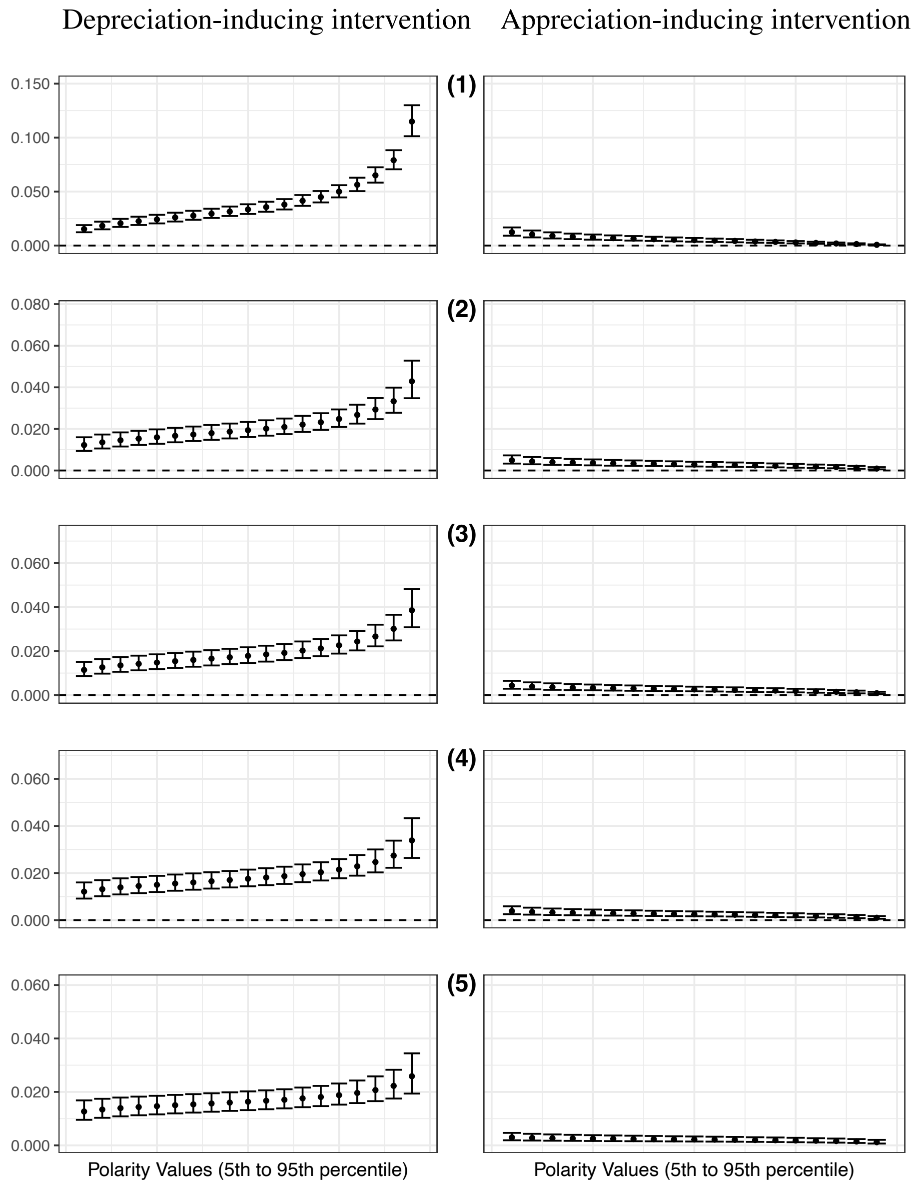


Figure A2: Predicted probability of depreciation-inducing (left column) and appreciation-inducing (right column) foreign exchange intervention.

A.4 Raw Exchange Rates

Table A3 shows the results for the ordered probit model after replacing the short/medium/long target exchange rates with the equivalent raw exchange rates. Figure A3 shows the predicted probability figures for the five models with standard errors computed with the delta method. The five models below correspond to Models 3 to 7 in the main paper.

Table A3: Ordered Probit Regression

	Dependent variable:				
	Forex Intervention (-1 buy local, sell foreign / 0 / +1 buy foreign, sell local)				
	(1)	(2)	(3)	(4)	(5)
Polarity (t-1)	1.240***	1.166***	1.108**	1.104*	1.116**
	(0.035)	(0.038)	(0.039)	(0.040)	(0.040)
Intervention (t-1)	9.812***	9.561***	9.211***	9.206***	9.427***
	(0.079)	(0.079)	(0.080)	(0.080)	(0.080)
ER Short (t-1)	0.553**	0.003***	0.001***	0.002***	0.002***
	(0.220)	(1.120)	(1.139)	(1.139)	(1.143)
ER Medium (t-20)		207.297***	26.668**	94.532***	175.422***
		(1.084)	(1.174)	(1.111)	(1.095)
ER Long (1 year mov.av.)			19.587***		
			(0.664)		
ER Long (3 year mov.av.)				5.396***	
				(0.393)	
ER Long (5 year mov.av.)					2.805**
					(0.336)
Pre-election (Binary)	0.824	0.832	0.843	0.822	0.823
	(0.150)	(0.153)	(0.153)	(0.152)	(0.152)
Post-election (Binary)	1.040	1.076	1.074	1.044	1.057
	(0.135)	(0.136)	(0.139)	(0.138)	(0.137)
Observations	6,605	6,605	6,605	6,605	6,605
Log Likelihood	−928.343	−916.175	−905.895	−906.616	−911.410
McFadden's Pseudo R^2	0.090	0.382	0.384	0.392	0.399

Note: Coefficient exponentiated. Standard errors in parentheses. *p<0.05; **p<0.01; ***p<0.001.

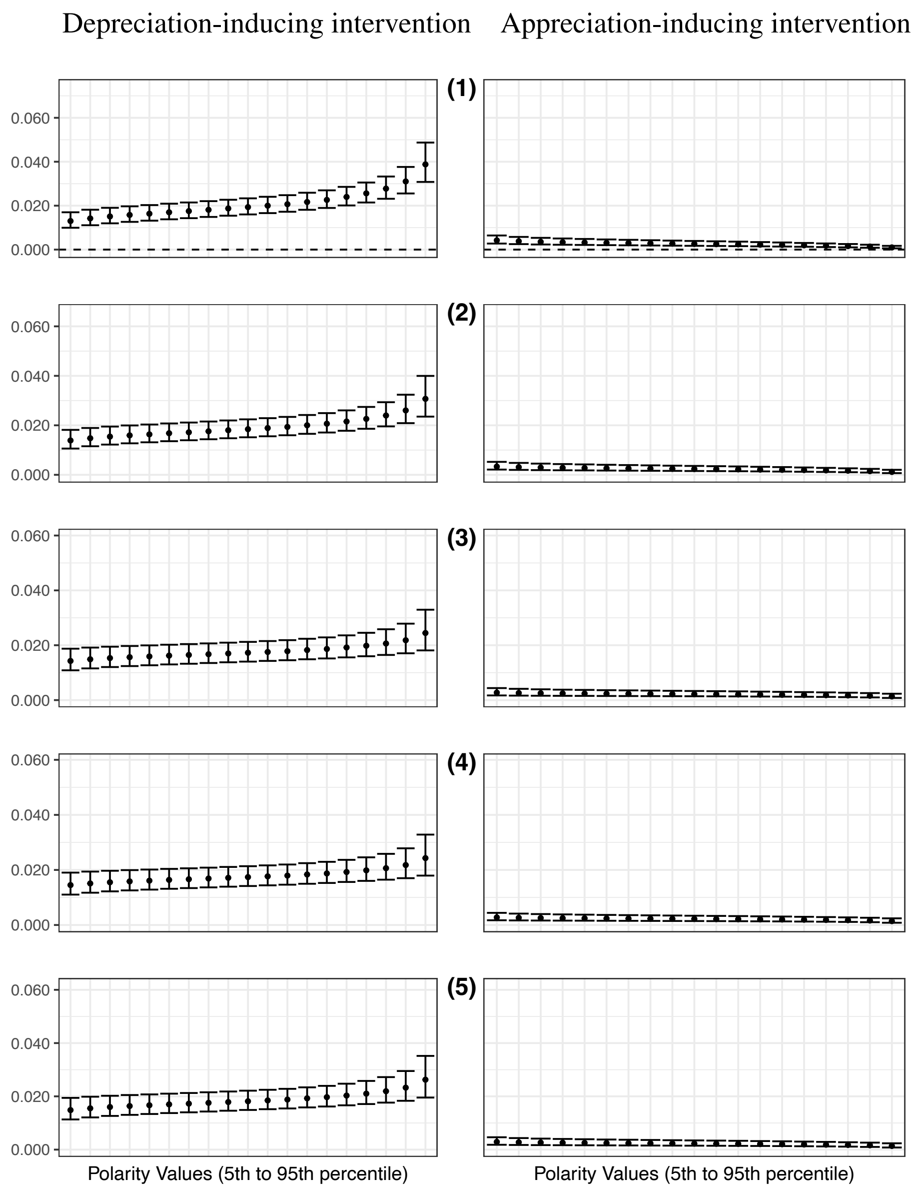


Figure A3: Predicted probability of depreciation-inducing (left column) and appreciation-inducing (right column) foreign exchange intervention.

A.5 Diagnostic Tests and Alternative Estimators

Table A4 shows the results from global and local Brant (1990) tests to detect possible violations of the proportional odds assumption (also known as the parallel regression assumption). The null hypothesis is that the assumption holds. As we can see, we fail to reject the null hypothesis globally across most models, except for Model 5 and 6. Locally, the short exchange rate target always violates the assumption, while the long exchange rate target does so except for when it is calculated based on the past five years' exchange rate. Our polarity measure yields a non-significant value, although it is just above the 0.05% threshold in Model 5 and 6.

Table A4: Brant Test (*p-values* displayed)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Omnibus	0.61	0.80	0.17	0.21	0.01	0.01	0.28
Polarity (t-1)	0.73	0.30	0.27	0.19	0.05	0.05	0.24
Pre-Election	0.37	0.60	0.66	0.68	0.68	0.58	0.59
Post-Election	0.37	0.59	0.59	0.55	0.53	0.63	0.54
Intervention (t-1)		0.93	0.77	0.90	0.86	0.86	0.85
ER Short			0.01	0.04	0.04	0.04	0.04
ER Medium				0.23	0.98	0.35	0.16
ER Long (1y)					0.01		
ER Long (3y)						0.01	
ER Long (5y)							0.87

We approach this issue in three different ways. First, for the models containing only one local violation (Model 4 and Model 7), we drop the offending variable, re-run the Brant test, and re-fit a simpler model that satisfies the proportional odds assumption. The results are similar to the original models and available in the replication package associated with this article.

Second, we relax the parallel regression assumption by estimating a set of stratified binomial models. We re-code the dependent variable as two binary indicators that capture the two events of interest (depreciation-inducing or appreciation-inducing) and re-run dynamic probit models on each dependent variable. Upon operationalizing the dependent variable this way, we would expect our polarity measure to be positively related to depreciation-inducing intervention and negatively related to appreciation-inducing intervention. This is what we find (see Table A5 and A6 for the regression output and Figure A4 and A5 for the predicted probability graphs).[57]

Third, we re-fit the main specifications in a multinomial logit regression framework, thus ignoring the order of the dependent variables. Tables A7 shows the results from this exercise. The reference category is no intervention. Once again, our lobbying proxy measure is positively related with depreciation-inducing foreign exchange intervention (relative risk ratio coefficient above 1) and negatively associated with appreciation-inducing interventions (relative risk ratio coefficient smaller than 1).

57. Recall that all coefficients are exponentiated so that a coefficient smaller than one indicates a negative relationship and a coefficient bigger than one indicates a positive relationship.

Table A5: Dynamic Probit Regression - Depreciation Inducing Intervention

	Dependent variable:						
	Forex Intervention (buy foreign, sell local)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Polarity (t-1)	1.579***	1.268***	1.252***	1.199***	1.099*	1.060	1.099*
	(0.029)	(0.037)	(0.039)	(0.041)	(0.046)	(0.046)	(0.043)
Intervention (t-1)		10.210***	11.031***	10.640***	10.530***	10.014***	9.921***
		(0.085)	(0.089)	(0.089)	(0.090)	(0.090)	(0.090)
ER Short Target			0.000***	0.000***	0.000***	0.000***	0.000***
			(4.476)	(4.664)	(4.747)	(4.780)	(4.691)
ER Medium Target				0.015***	0.015***	0.034**	0.306
				(1.252)	(1.281)	(1.304)	(1.334)
ER Long Target (1 year mov.av.)					0.235***		
					(0.355)		
ER Long Target (3 year mov.av.)						0.057***	
						(0.469)	
ER Long Target (5 year mov.av.)							0.008***
							(0.795)
Pre-election (Binary)	0.735	0.807	0.791	0.812	0.780	0.756	0.785
	(0.161)	(0.191)	(0.200)	(0.199)	(0.203)	(0.208)	(0.215)
Post-election (Binary)	1.075	1.082	1.120	1.147	1.124	1.103	1.154
	(0.124)	(0.151)	(0.152)	(0.152)	(0.155)	(0.159)	(0.163)
Constant	0.118***	0.098***	0.094***	0.096***	0.093***	0.092***	0.094***
	(0.045)	(0.055)	(0.058)	(0.058)	(0.061)	(0.062)	(0.061)
Observations	6,664	6,664	6,580	6,580	6,580	6,580	6,580
Log Likelihood	−1,148.295	−741.917	−711.290	−705.868	−697.366	−684.777	−686.614
McFadden's Pseudo R^2	0.103	0.421	0.442	0.446	0.452	0.462	0.461

Note: Coefficients exponentiated. Standard errors in parentheses. *p<0.05; **p<0.01; ***p<0.001.

Table A6: Dynamic Probit Regression - Appreciation Inducing Intervention

	Dependent variable:						
	Forex Intervention (buy local, sell foreign)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Polarity (t-1)	0.705***	0.695**	0.696**	0.698**	0.661**	0.681**	0.743*
	(0.106)	(0.118)	(0.117)	(0.123)	(0.135)	(0.135)	(0.132)
Intervention (t-1)		7.719***	7.792***	7.793***	7.784***	7.811***	7.586***
		(0.226)	(0.228)	(0.228)	(0.228)	(0.228)	(0.228)
ER Short Target			151.956	133.658	94.378	105.313	278.886
			(9.122)	(9.327)	(9.334)	(9.343)	(9.264)
ER Medium Target				1.187	3.213	1.460	0.784
				(2.376)	(2.530)	(2.415)	(2.378)
ER Long Target (1 year mov.av.)					0.237		
					(1.297)		
ER Long Target (3 year mov.av.)						0.744	
						(0.667)	
ER Long Target (5 year mov.av.)							2.332
							(0.574)
Pre-election (Binary)	0.970	1.048	1.061	1.061	1.089	1.062	1.054
	(0.266)	(0.275)	(0.273)	(0.273)	(0.274)	(0.273)	(0.276)
Post-election (Binary)	1.155	1.101	1.093	1.093	1.104	1.087	1.110
	(0.225)	(0.251)	(0.253)	(0.253)	(0.257)	(0.254)	(0.251)
Constant	0.098***	0.088***	0.088***	0.088***	0.090***	0.089***	0.086***
	(0.082)	(0.091)	(0.092)	(0.096)	(0.099)	(0.100)	(0.099)
Observations	6,664	6,664	6,580	6,580	6,580	6,580	6,580
Log Likelihood	−227.687	−192.819	−192.258	−192.256	−191.663	−192.158	−191.202
McFadden's Pseudo R^2	0.028	0.177	0.178	0.178	0.180	0.178	0.182

Note: Coefficients exponentiated. Standard errors in parentheses. *p<0.05; **p<0.01; ***p<0.001.

Table A7: Multinomial Regression - Model 1

	Dependent variable:	
	Appreciation-Inducing	Depreciation-Inducing
	(1)	(2)
Polarity (t-1)	0.387**	2.402***
	(0.290)	(0.055)
Pre-election (Binary)	0.954	0.499
	(0.732)	(0.373)
Post-election (Binary)	1.494	1.214
	(0.607)	(0.261)
Constant	0.010***	0.020***
	(0.218)	(0.097)
Observations	6,605	6,605
Log Likelihood	-1379.803	-1379.803
McFadden's Pseudo R^2	0.103	0.103

Note: Coefficients exponentiated. Standard errors in parentheses. *p<0.05; **p<0.01; ***p<0.001.

Predicted Probabilities - Simple Probit

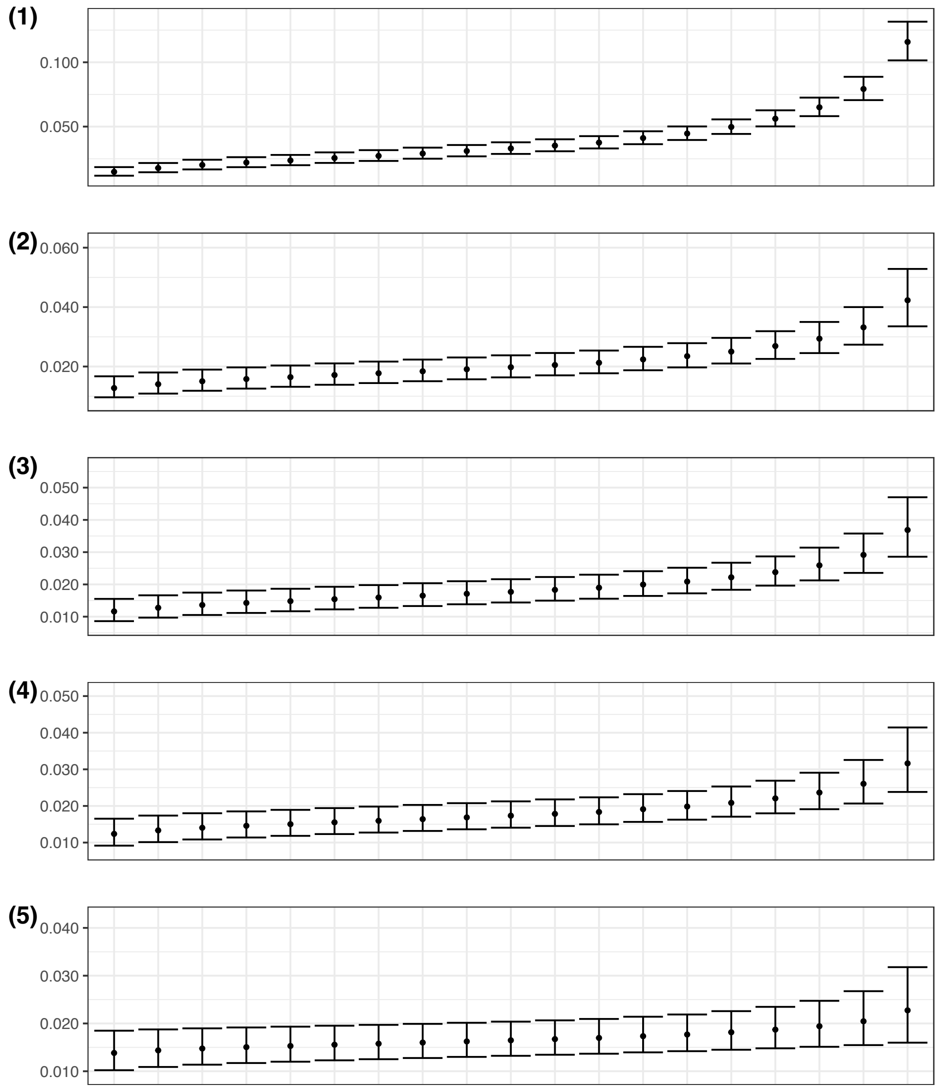


Figure A4: Predicted probability of depreciation-inducing foreign exchange intervention

Predicted Probabilities - Simple Probit

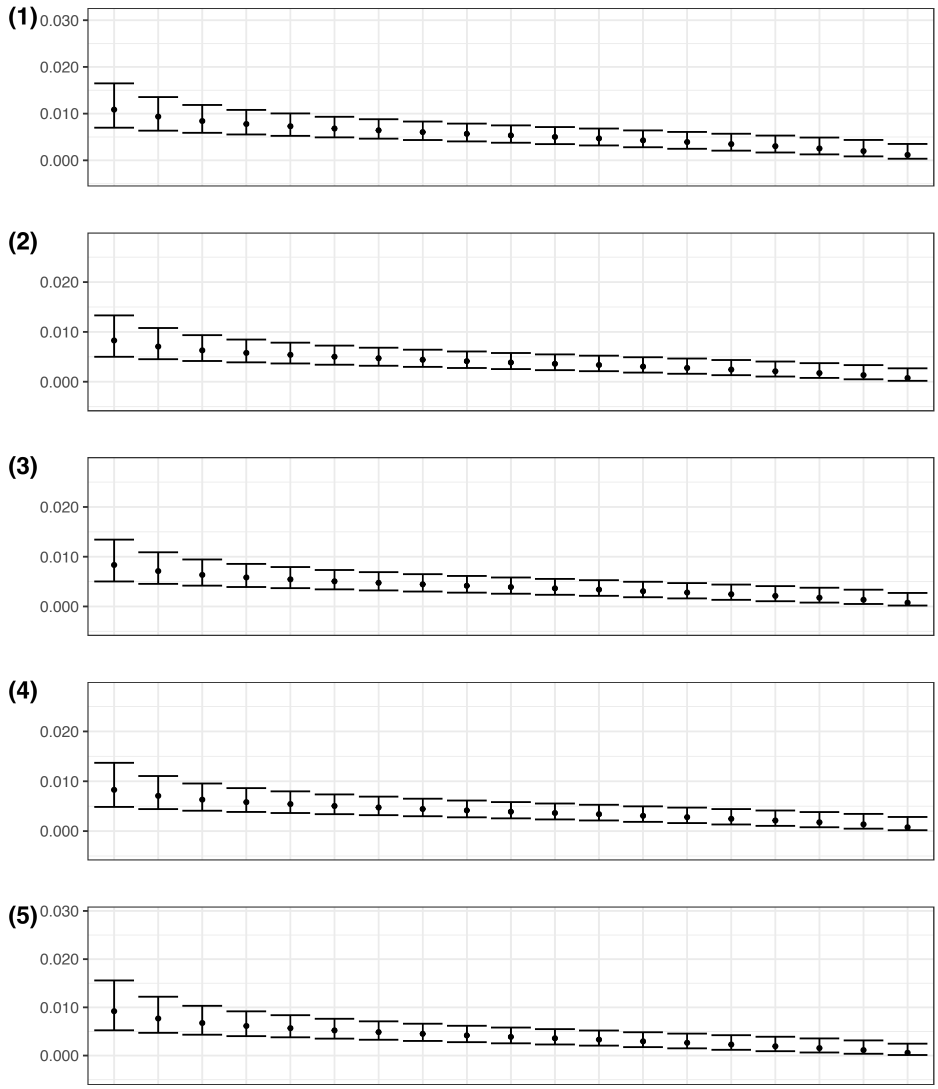


Figure A5: Predicted probability of appreciation-inducing foreign exchange intervention.

A.6 Data-driven Variable Selection

Here, we further investigate the extent to which our polarity variable matters relative to the other covariates in the model. In Table A8, we fit a set of stepwise dynamic ordinal probit regressions, a data-driven variable selection process where predictors are added or removed from the initial model (full model) based on minimizing the AIC criterion. As we can see, the stepwise algorithm always keeps our polarity measure in the model.[58]

Table A8: AIC Stepwise Dynamic Ordinal Probit - Full Models

	Dependent variable:		
	Forex Intervention (-1 buy local, sell foreign / 0 / +1 buy foreign, sell local)		
	(1)	(2)	(3)
Polarity (t-1)	1.154***	1.119**	1.132**
	(0.038)	(0.040)	(0.041)
Intervention (t-1)	9.851***	9.828***	10.069***
	(0.082)	(0.082)	(0.082)
ER Short Target	0.000***	0.000***	0.000***
	(4.095)	(4.261)	(4.260)
ER Long Target (1 year mov.av.)	0.032***		
	(0.614)		
ER Medium Target		0.062*	0.034**
		(1.150)	(1.139)
ER Long (3 year mov.av.)		0.160***	
		(0.362)	
ER Long (5 year mov.av.)			0.290***
			(0.302)
Observations	6,580	6,580	6,580
Log Likelihood	−891.552	−889.349	−894.256

Note: Coefficients exponentiated. Standard errors in parentheses. *p<0.05; **p<0.01; ***p<0.001.

In Table A7, we take this analysis a step further by performing extreme bounds analysis (EBA) (Hlavac 2016). We show the results relying on the original version by (Leamer 1985), which fo-

58. Unsurprisingly, the algorithm always excludes the two election binary variables, which have low predictive power. We obtain essentially the same results if we exclude the two election dummies before running the stepwise regressions.

cuses on the upper and lower extreme bounds of regression estimates, as well as the more flexible framework proposed by Sala-I-Martin (1997). Rather than focusing only on the coefficients that yield the upper and lower extreme bounds, Sala-i-Martin's EBA considers the full distribution of regression coefficients. For the latter, we rely on the generic version of the test, which makes no assumption about the distribution of coefficients.[59] To give greater weight to models that provide a better fit, we follow Hegre and Sambanis (2006), among others, and weight each regression coefficient according to the McFadden's likelihood ratio index. The algorithm fits 127 linear regressions (2^7 minus one empty set) starting from the full model (with the 1-year moving average as the long target), extract each value of interest (coefficients, standard errors, likelihood ratio test), and computes the summary statistics. The results using the two other measures of long targets are substantially similar. We rely on OLS for two reasons. First, it is computationally less demanding than ordered categorical models. Second, doing so allows us to use Newey-West standard errors, which are robust to heteroskedasticity and serial correlation (and cannot be easily computed for ordered probit models).

As the first two rows in the table show, the weighted mean, maximum, and minimum of the regression coefficients across all 127 regressions are positive and in line with the main analysis. The coefficient for polarity is positive and statistically significant across all models. As the lower extreme bound is also positive (row three), the polarity score can be labeled as "robust" according to Leamer's procedure. We come to the same conclusion after assessing the full distribution of coefficients across all models (row four).

59. Visual inspection of the coefficients distributions from 127 different combinations of the regressors shows that they are not normally distributed.

Table A9: EBA Regression Results

			Beta Coefficients			
	β (Wgt Mean)	**SE (Wgt Mean)**	**Min β**	**SE (Min β)**	**Max β**	**SE (Max β)**
Polarity (t-1)	0.026	0.007	0.017	0.006	0.073	0.013
			Distribution of beta coefficients			
	%($\beta < 0$)	**%($\beta > 0$)**	**%(significant)**	**%(signif and $\beta < 0$)**	**%(signif and $\beta > 0$)**	
Polarity (t-1)	0.000	100.000	100.000	0.000	100.000	
			Leamer's Extreme Bounds Analysis (EBA)			
		Lower Extreme Bound		**Upper Extreme Bound**	**Robust/Fragile?**	
Polarity (t-1)		0.004		0.098	Robust	
			Sala-i-Martin's Extreme Bounds Analysis (EBA)			
		CDF($\beta <= 0$)		**CDF($\beta > 0$)**	**Robust/Fragile?**	
Polarity (t-1)		0.202		99.798	Robust	

Note: Based on Newey West standard errors.

A.7 Marginal Effects and Heteroskedastic Models

In the paper, we showed the predicted probabilities of foreign exchange interventions at selected values of our focus variable. Relatedly, one may wonder about the marginal effects of polarity on each outcome value. Table A10 shows the marginal effects for the full model (Model 5). The values are multiplied by 100 and can be interpreted as percentage points effects. In other words, a one unit increase in the polarity score is associated with a 0.09 percentage points decrease in the probability of appreciation-inducing intervention and a 0.58 percentage points increase in the probability of depreciation inducing intervention. These are non-trivial effects if we consider that the unconditional probability of a depreciation and appreciation-inducing intervention occurring on any given day is 4.79% and 0.57%, respectively.

Table A10: Ordered Probit Models Marginal Effects (Model 5)

	Appreciation-inducing	No intervention	Depreciation-inducing
Polarity (t-1)	-0.09**	-0.49***	0.58***
	(0.03)	(0.14)	(0.17)

Note: Standard errors delta method in parentheses. *p<0.05; **p<0.01; ***p<0.001.

Finally, it should be noted that under standard ordered probit models the variance of the error term is assumed to be homoskedastic. Nevertheless, the observation that appreciation- and depreciation- inducing interventions are not (unconditionally) equally likely to occur already suggests a possible violation of this assumption. One may expect the target exchange rates (i.e. the deviations from past levels of the exchange rates) to have different effects depending on whether the currency is appreciated or depreciated relative to some function of the historical level. Similarly, the political business cycle may affect one type of intervention more than the other. As such, we re-fit the full models using heteroskedastic probit models. The mean equation remains the same as before. The variance equation includes the three target exchange rates as well as the two election dummies. Unlike in the case of homoskedastic models, the sign of the coefficient(s) in heteroskedastic models is uninformative and may not be consistent with the sign of the marginal effects and predicted probabilities. Hence, we show only the marginal effects in Table A11. The results are consistent with the main analysis and, if anything, slightly stronger in size.[60]

Table A11: Heteroskedastic Ordered Probit Models Marginal Effects (Model 5)

	Appreciation-inducing	No intervention	Depreciation-inducing
Polarity (t-1)	-0.13**	-0.47***	0.59***
	(0.04)	(0.14)	(0.16)

Note: Standard errors delta method in parentheses. *p<0.05; **p<0.01; ***p<0.001.

60. Moreover, a likelihood ratio test comparing the homoskedastic probit to the heteroskedastic probit shows that the latter leads to a significant improvement in model fit.

A.8 Volume of Intervention

As discussed in the paper, using the volume of intervention as the dependent variable has its drawbacks: As monetary authorities may adjust the size of successive interventions within a single day based on the reaction of the exchange rate to earlier intervention, using the intervention amount introduces an endogeneity issue. Relying on a three-level ordinal categorical variable, as we do in the paper, can mitigate this problem, but comes at the cost of a loss of information. To further probe the robustness of the results, Table A12 below shows the results for the linear models with the volume of intervention as the dependent variable. The volume has been rescaled for interpretation so that a one-unit change in the independent variable corresponds to a one-million yen intervention. Positive numbers indicate purchases of dollars (i.e. depreciation-inducing interventions). Since the amount of intervention can be treated as continuous, we fit seven linear models following the same specification as in the main paper. The conclusions are the same, with one exception: the pre-election coefficients are now significant, suggesting that the amount of an intervention prior to an election is reduced.

Similarly, Table A13 presents the results using the same linear models on a seven-level ordinal categorical dependent variable based on intervention volume. The data is divided into terciles, conditional on the intervention's direction. Specifically, the new dependent variable is assigned a value of -3 for the lowest tercile of appreciation-inducing interventions, -2 for the middle tercile, and -1 for the highest tercile. A value of zero represents no intervention, while depreciation-inducing interventions are coded as the mirror image of appreciation-inducing ones. This approach preserves additional information about the intensity of interventions while addressing endogeneity concerns by using a discrete indicator with daily data as a middle-ground solution retaining richer information. Table A14 shows the results hold using the same dynamic ordinal probit models as in the main paper.

Table A12: Linear Models with Amount of Intervention as Dependent Variable

	Dependent variable:						
	Forex Intervention Volume in 1 Mln Yen ((+) numbers mean purchases of the USD (sell Yen))						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Polarity (t-1)	0.989**	0.887**	0.844**	0.644*	0.588*	0.319	0.471*
	(0.308)	(0.327)	(0.327)	(0.305)	(0.243)	(0.277)	(0.236)
Intervention Amount (t-1)		0.108*	0.113*	0.111*	0.111*	0.110*	0.111*
		(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)
ER Short Target			−93.148**	−76.774**	−76.620**	−75.588**	−76.173**
			(29.894)	(29.124)	(29.136)	(29.067)	(29.185)
ER Medium Target				−16.485*	−17.514*	−14.325*	−16.099*
				(6.500)	(7.059)	(6.434)	(6.425)
ER Long Target (1 year mov.av.)					−1.303		
					(1.830)		
ER Long Target (3 year mov.av.)						−4.852**	
						(1.747)	
ER Long Target (5 year mov.av.)							−2.335**
							(1.740)
Pre-election (Binary)	−1.049***	−0.938***	−0.950***	−0.966***	−0.985***	−0.990***	−0.995***
	(0.257)	(0.241)	(0.245)	(0.248)	(0.263)	(0.273)	(0.265)
Post-election (Binary)	−0.517	−0.457	−0.435	−0.414	−0.428	−0.426	−0.434
	(0.466)	(0.417)	(0.418)	(0.430)	(0.442)	(0.430)	(0.435)
Observations	6,664	6,664	6,580	6,580	6,580	6,580	6,580
R Squared	0.003	0.014	0.016	0.017	0.017	0.018	0.017

Note: Newey West Standard Errors in Parentheses. *p< 0.05; **p< 0.01; ***p< 0.001.

Table A13: Linear Models with Seven Category Intensity as Dependent Variable

	Dependent variable:						
	Seven Category Intensity Forex Intervention ((+) numbers mean purchases of the USD (sell Yen))						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Polarity (t-1)	0.119^{***}	0.048^{***}	0.045^{***}	0.038^{***}	0.026^{*}	0.026^{*}	0.032^{**}
	(0.021)	(0.012)	(0.011)	(0.011)	(0.013)	(0.013)	(0.012)
Intervention Seven Categories (t-1)		0.542^{***}	0.546^{***}	0.544^{***}	0.541^{***}	0.542^{***}	0.543^{***}
		(0.041)	(0.041)	(0.041)	(0.040)	(0.041)	(0.041)
ER Short Target			-5.741^{***}	-5.172^{***}	-5.119^{***}	-5.130^{***}	-5.151^{***}
			(1.156)	(1.134)	(1.128)	(1.127)	(1.132)
ER Medium Target				-0.576^{*}	-0.307	-0.496^{*}	-0.561^{*}
				(0.232)	(0.254)	(0.233)	(0.231)
ER Long Target (1 year mov.av.)					-0.394^{**}		
					(0.124)		
ER Long Target (3 year mov.av.)						-0.183^{**}	
						(0.059)	
ER Long Target (5 year mov.av.)							-0.088^{*}
							(0.041)
Pre-election (Binary)	-0.060^{**}	-0.034^{**}	-0.033^{**}	-0.034^{**}	-0.029^{*}	-0.035^{**}	-0.035^{**}
	(0.022)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
Post-election (Binary)	-0.009	0.002	0.003	0.004	0.009	0.003	0.003
	(0.042)	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)	(0.021)
Observations	6,664	6,664	6,580	6,580	6,580	6,580	6,580
R Squared	0.034	0.315	0.321	0.322	0.324	0.323	0.323

Note: Newey West Standard Errors in Parenthesis. *p<0.05; **p<0.01; ***p<0.001.

Table A14: Ordered Probit Regression - Seven-Level Category

	Dependent variable:						
	Seven Category Intensity Forex Intervention ((+) numbers mean purchases of the USD (sell Yen))						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Polarity (t-1)	1.476***	1.303***	1.287***	1.234***	1.157***	1.127***	1.140***
	(0.026)	(0.029)	(0.029)	(0.032)	(0.034)	(0.035)	(0.036)
Intervention (t-1)		2.455***	2.521***	2.492***	2.448***	2.461***	2.493***
		(0.032)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
ER Short Target			0.000***	0.000***	0.000***	0.000***	0.000***
			(3.804)	(3.944)	(3.949)	(3.984)	(3.981)
ER Medium Target				0.024***	0.216	0.056**	0.030***
				(1.043)	(1.118)	(1.072)	(1.060)
ER Long Target (1 year mov.av.)					0.037***		
					(0.614)		
ER Long Target (3 year mov.av.)						0.139***	
						(0.342)	
ER Long Target (5 year mov.av.)							0.271***
							(0.283)
Pre-election (Binary)	0.791	0.859	0.830	0.838	0.852	0.824	0.826
	(0.123)	(0.140)	(0.144)	(0.145)	(0.146)	(0.146)	(0.146)
Post-election (Binary)	0.992	1.046	1.066	1.082	1.075	1.044	1.057
	(0.113)	(0.126)	(0.127)	(0.127)	(0.130)	(0.130)	(0.129)
Observations	6,664	6,664	6,580	6,580	6,580	6,580	6,580
Log Likelihood	−1,792.414	−1,406.507	−1,375.314	−1,368.931	−1,353.933	−1,351.295	−1,358.023
McFadden's Pseudo R^2	0.059	0.262	0.275	0.278	0.286	0.288	0.284

Note: Coefficients exponentiated. Standard errors in parentheses. *p<0.05; **p<0.01; ***p<0.001.

A.9 Exchange Market Pressure, Interest Rates, and the Real Effective Exchange Rate

We present some additional robustness checks to see if the results hold after controlling for a real effective rather than the nominal exchange rate change, reasoning that price levels are ultimately the determining factor of export competitiveness, although nominal and real rates tend to move in tandem, and if we account for exchange market pressure. We also probe if the Japanese monetary authorities possibly target the interest rate rather than the exchange rate in response to industry pressure. To do this we estimate models using the Central Bank Discount Rate as dependent variable. All these measures are available only at monthly frequency.

As a sanity check, we start by re-estimating the same models after aggregating at the monthly level. Table A15 shows that the results hold across all specifications. To construct the monthly dataset, we follow Ito and Yabu (2020) and calculate the short and long target exchange rate in a similar fashion. The short target exchange rate is now based on the the difference between the nominal exchange rate lagged by one month and the exchange rate two months prior. The medium target is not calculated as it would be the same as the short target. The long targets are still based on Eq. 1 in the paper after substituting the 260 business days with 12 months per year. The binary indicators for pre- and post- election take the value of one the month before and after an election, respectively.

Table A15: Ordered Probit Regression - Monthly

	Dependent variable:					
	Forex Intervention (-1 buy local, sell foreign / 0 / +1 buy foreign, sell local)					
	(1)	(2)	(3)	(4)	(5)	(6)
Polarity (t-1)	4.610***	2.245***	2.337***	2.435**	2.322**	2.483**
	(0.203)	(0.231)	(0.248)	(0.286)	(0.315)	(0.314)
Intervention (t-1)		5.240***	5.228***	5.226***	5.230***	5.209***
		(0.204)	(0.204)	(0.204)	(0.204)	(0.204)
ER Short Target			5.639	3.840	5.625	6.958
			(3.752)	(3.976)	(3.753)	(3.809)
ER Long Target (1 year mov.av.)				1.873		
				(2.141)		
ER Long Target (3 year mov.av.)					0.963	
					(1.178)	
ER Long Target (5 year mov.av.)						1.368
						(0.982)
Pre-election (Binary)	0.987	0.955	0.952	0.948	0.952	0.957
	(0.347)	(0.406)	(0.407)	(0.406)	(0.407)	(0.407)
Post-election (Binary)	0.784	0.629	0.627	0.622	0.627	0.628
	(0.351)	(0.387)	(0.388)	(0.389)	(0.388)	(0.388)
Observations	307	307	307	307	307	307
Log Likelihood	−164.120	−128.719	−128.612	−128.569	−128.612	−128.561
McFadden's Pseudo R^2	0.196	0.369	0.370	0.370	0.370	0.370

Note: Coefficients exponentiated. Standard errors in parentheses. *p<0.05; **p<0.01; ***p<0.001.

Next, we rerun the models including the exchange market pressure (EMP) index for the Japanese yen. We collect the data from Patnaik, Felman, and Shah (2017). We start by simply adding the index as control variable in all models. Unfortunately, this data is only available for the 1995-2013 period, thus reducing the size of the dataset. Table A16 shows that the results hold for all models except one.

The EMP is constructed based on the change in the exchange rate and the counterfactual that we would expect under no central bank intervention (for the details, see Patnaik et al., (2017). As such, it already incorporates information contained in the exchange rate, at least in the short term, as well as in the lagged interventions, thus raising the issue of multicollinearity and attenuation bias. To avoid it, we rerun the models after excluding the short target first (Table A17), and then both the short target the lagged intervention variable (Table A18).

Finally, the authors also provide the upper and lower bounds of their estimates of Exchange Market Pressure. To ensure that our results are robust to measurement error, we re-fit the final models (without the lagged dependent variable and the short target exchange rate) after substituting the mean EMP index with its low (Table A19) and high estimates (Table A20).

Table A16: Ordered Probit Regression - Controlling for Exchange Market Pressure (I)

	Dependent variable:					
	Forex Intervention (-1 buy local, sell foreign / 0 / +1 buy foreign, sell local)					
	(1)	(2)	(3)	(4)	(5)	(6)
Polarity (t-1)	4.059***	2.623**	2.554**	2.127*	1.983	2.502*
	(0.298)	(0.318)	(0.332)	(0.362)	(0.381)	(0.430)
EMP (t-1)	0.993	1.014	1.015	1.013	1.014	1.015
	(0.009)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Intervention (t-1)		4.326***	4.337***	4.138***	4.222***	4.343***
		(0.276)	(0.276)	(0.279)	(0.276)	(0.276)
ER Short Target			0.311	2.154	0.303	0.289
			(4.445)	(4.761)	(4.478)	(4.551)
ER Long Target (1 year mov.av.)				0.048		
				(2.670)		
ER Long Target (3 year mov.av.)					0.175	
					(1.458)	
ER Long Target (5 year mov.av.)						0.908
						(1.288)
Pre-election (Binary)	1.039	0.943	0.947	0.970	0.927	0.946
	(0.448)	(0.514)	(0.513)	(0.521)	(0.519)	(0.514)
Post-election (Binary)	0.612	0.485	0.487	0.501	0.482	0.487
	(0.464)	(0.489)	(0.489)	(0.491)	(0.492)	(0.489)
Observations	216	216	216	216	216	216
Log Likelihood	−102.793	−88.063	−88.028	−87.373	−87.300	−88.025
McFadden's Pseudo R^2	0.161	0.282	0.282	0.287	0.288	0.282

Note: Coefficients exponentiated. Standard errors in parentheses. *p<0.05; **p<0.01; ***p<0.001.

Table A17: Ordered Probit Regression - Controlling for Exchange Market Pressure (II)

	Dependent variable:				
	Forex Intervention (-1 buy local / 0 / +1 buy foreign)				
	(1)	(2)	(3)	(4)	(5)
Polarity (t-1)	4.059^{***}	2.623^{**}	2.114^{*}	2.035	2.611^{*}
	(0.298)	(0.318)	(0.360)	(0.371)	(0.403)
EMP (t-1)	0.993	1.014	1.014	1.013	1.014
	(0.009)	(0.011)	(0.011)	(0.011)	(0.011)
Intervention (t-1)		4.326^{***}	4.154^{***}	4.210^{***}	4.327^{***}
		(0.276)	(0.277)	(0.276)	(0.276)
ER Long Target (1 year mov.av.)			0.056		
			(2.499)		
ER Long Target (3 year mov.av.)				0.175	
				(1.459)	
ER Long Target (5 year mov.av.)					0.978
					(1.261)
Pre-election (Binary)	1.039	0.943	0.971	0.923	0.943
	(0.448)	(0.514)	(0.520)	(0.520)	(0.514)
Post-election (Binary)	0.612	0.485	0.501	0.481	0.485
	(0.464)	(0.489)	(0.491)	(0.493)	(0.489)
Observations	216	216	216	216	216
Log Likelihood	−102.793	−88.063	−87.386	−87.336	−88.063
McFadden's Pseudo R^2	0.161	0.282	0.287	0.288	0.282

Note: Coefficients exponentiated. Standard errors in parentheses. *p<0.05; **p<0.01; ***p<0.001.

Table A18: Ordered Probit Regression - Controlling for Exchange Market Pressure (III)

	Dependent variable:			
	Forex Intervention (-1 buy local / 0 / +1 buy foreign)			
	(1)	(2)	(3)	(4)
Polarity (t-1)	4.059***	2.885**	2.888**	4.407***
	(0.298)	(0.346)	(0.359)	(0.383)
EMP (t-1)	0.993	0.993	0.992	0.993
	(0.009)	(0.009)	(0.009)	(0.009)
ER Long Target (1 year mov.av.)		0.014		
		(2.384)		
ER Long Target (3 year mov.av.)			0.113	
			(1.373)	
ER Long Target (5 year mov.av.)				1.503
				(1.188)
Pre-election (Binary)	1.039	1.084	1.015	1.044
	(0.448)	(0.456)	(0.453)	(0.449)
Post-election (Binary)	0.612	0.642	0.610	0.610
	(0.464)	(0.469)	(0.467)	(0.465)
Observations	216	216	216	216
Log Likelihood	−102.793	−101.127	−101.502	−102.735
McFadden's Pseudo R^2	0.161	0.175	0.1752	0.162

Note: Coefficients exponentiated. Standard errors in parentheses. *p<0.05; **p<0.01; ***p<0.001.

Table A19: Ordered Probit Regression - Controlling for Exchange Market Pressure (IV)

	Dependent variable:			
	Forex Intervention (-1 buy local / 0 / +1 buy foreign)			
	(1)	(2)	(3)	(4)
Polarity (t-1)	3.623***	2.340*	2.803**	5.107***
	(0.328)	(0.381)	(0.397)	(0.429)
EMP (low) (t-1)	0.915***	0.916***	0.916***	0.913***
	(0.014)	(0.014)	(0.014)	(0.014)
ER Long Target (1 year mov.av.)		0.003*		
		(2.953)		
ER Long Target (3 year mov.av.)			0.186	
			(1.562)	
ER Long Target (5 year mov.av.)				5.589
				(1.339)
Pre-election (Binary)	0.804	0.855	0.785	0.824
	(0.546)	(0.566)	(0.553)	(0.548)
Post-election (Binary)	0.548	0.595	0.554	0.526
	(0.523)	(0.530)	(0.522)	(0.530)
Observations	216	216	216	216
Log Likelihood	−73.058	−70.898	−72.465	−72.231
McFadden's Pseudo R^2	0.411	0.428	0.436	0.428

Note: Coefficients exponentiated. Standard errors in parentheses. *p<0.05; **p<0.01; ***p<0.001.

Table A20: Ordered Probit Regression - Controlling for Exchange Market Pressure (IV)

	Dependent variable:			
	Forex Intervention (-1 buy local / 0 / +1 buy foreign)			
	(1)	(2)	(3)	(4)
Polarity (t-1)	6.282***	4.745***	4.324***	5.404***
	(0.323)	(0.377)	(0.382)	(0.392)
EMP (high) (t-1)	0.951***	0.953***	0.950***	0.949***
	(0.014)	(0.014)	(0.014)	(0.014)
ER Long Target (1 year mov.av.)		0.034		
		(2.442)		
ER Long Target (3 year mov.av.)			0.081	
			(1.434)	
ER Long Target (5 year mov.av.)				0.427
				(1.261)
Pre-election (Binary)	0.957	0.994	0.931	0.943
	(0.459)	(0.466)	(0.466)	(0.460)
Post-election (Binary)	0.535	0.556	0.525	0.535
	(0.498)	(0.501)	(0.503)	(0.499)
Observations	216	216	216	216
Log Likelihood	−97.421	−96.443	−95.840	−97.192
McFadden's Pseudo R^2	0.215	0.222	0.227	0.216

Note: Coefficients exponentiated. Standard errors in parentheses. *p<0.05; **p<0.01; ***p<0.001.

In the next set of specifications, we control for the real effective exchange rate (REER). The REER data comes from Darvas (2021). We use the measure based on 51 trading partners as it is the only one covering the full period under study. First, we simply add the lagged REER as a further control variable. Table A21 shows the results. Once again, the REER already contains some information from the nominal exchange rate which is used to construct the short target, thus possibly resulting in multicollinearity and attenuation bias. As such, we re-calculate the short and long exchange rate targets based on the REER (rather than the nominal exchange rate) and re-fit the models controlling for the "REER Targets." As shown in Table A22, the results across all six models.

Table A21: Ordered Probit Regression - Controlling for the Real Effective Exchange Rate (I)

	Dependent variable:					
	Forex Intervention (-1 buy local, sell foreign / 0 / +1 buy foreign, sell local)					
	(1)	(2)	(3)	(4)	(5)	(6)
Polarity (t-1)	3.486***	1.902*	1.925*	2.001*	2.039*	2.124*
	(0.232)	(0.255)	(0.281)	(0.315)	(0.330)	(0.331)
REER (t-1)	1.015*	1.011	1.010	1.010	1.011	1.011
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Intervention (t-1)		5.058***	5.058***	5.057***	5.026***	5.007***
		(0.205)	(0.205)	(0.205)	(0.206)	(0.206)
ER Short Target			1.500	1.051	1.437	2.038
			(3.891)	(4.107)	(3.892)	(3.925)
ER Long Target (1 year mov.av.)				1.793		
				(2.145)		
ER Long Target (3 year mov.av.)					1.506	
					(1.220)	
ER Long Target (5 year mov.av.)						1.781
						(1.002)
Pre-election (Binary)	0.971	0.951	0.950	0.947	0.955	0.960
	(0.352)	(0.410)	(0.410)	(0.410)	(0.410)	(0.410)
Post-election (Binary)	0.774	0.622	0.622	0.618	0.624	0.624
	(0.351)	(0.385)	(0.385)	(0.386)	(0.386)	(0.385)
Observations	307	307	307	307	307	307
Log Likelihood	−160.963	−127.529	−127.523	−127.486	−127.467	−127.357
McFadden's Pseudo R^2	0.211	0.375	0.375	0.375	0.375	0.376

Note: Coefficients exponentiated. Standard errors in parentheses. *p<0.05; **p<0.01; ***p<0.001.

Table A22: Ordered Probit Regression - Controlling for the Real Effective Exchange Rate (II)

	Dependent variable:					
	Forex Intervention (-1 buy local, sell foreign / 0 / +1 buy foreign, sell local)					
	(1)	(2)	(3)	(4)	(5)	(6)
Polarity (t-1)	4.610***	2.245***	2.322***	2.628***	2.485***	2.012*
	(0.203)	(0.231)	(0.244)	(0.252)	(0.266)	(0.276)
Intervention (t-1)		5.240***	5.224***	5.418***	5.325***	5.039***
		(0.204)	(0.204)	(0.207)	(0.207)	(0.206)
REER Short Target			0.987	0.999	0.987	0.990
			(0.029)	(0.030)	(0.029)	(0.030)
REER Long Target (1 year mov.av.)				0.953*		
				(0.024)		
REER Long Target (3 year mov.av.)					0.990	
					(0.016)	
REER Long Target (5 year mov.av.)						1.013
						(0.012)
Pre-election (Binary)	0.987	0.955	0.943	0.996	0.942	0.937
	(0.347)	(0.406)	(0.407)	(0.407)	(0.405)	(0.410)
Post-election (Binary)	0.784	0.629	0.627	0.623	0.624	0.621
	(0.351)	(0.387)	(0.388)	(0.388)	(0.388)	(0.388)
Observations	307	307	307	307	307	307
Log Likelihood	−164.120	−128.719	−128.618	−126.541	−128.412	−128.031
McFadden's Pseudo R^2	0.196	0.369	0.370	0.380	0.371	0.373

Note: Coefficients exponentiated. Standard errors in parentheses. *p<0.05; **p<0.01; ***p<0.001.

Finally, central bank intervention is not the only way to improve the competitiveness of exporting firms. In the following, we replace our dependent variable with the Central Bank Discount Rate, i.e. the interest rate that a central bank charges commercial banks and financial institutions for borrowing funds, typically through short-term loans. The standard uncovered interest parity condition implies that a lower interest rate will lead to an expectation of depreciation. The data comes from FRED St. Louis and is available for the full period. Table A23 shows the results for the models with the discount rate in levels. The discount rate is expressed in percentage points and ranges from a minimum of 0.10 to a maximum of 6.00 with a mean of 1.14 and a standard deviation of 1.58. The models show a small but precisely estimated (except for Model 1) decrease in the discount interest rate. Nevertheless, the discount interest rate is a slow-moving variable, changing its value only 29 times in our sample. As such, it is likely better to directly model the change in the interest rate. In Table A24 we replace the interest rate in levels with its first difference and rerun the models. The change in the discount rate ranges from a minimum 0f -0.75 to a maximum of 1.00 with a mean of -0.007 and a standard deviation of 0.14.

Table A23: Linear Models - Discount Interest Rate (I)

	Dependent variable:					
	Discount Interest Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Polarity (t-1)	−0.181	−0.051**	−0.055**	−0.055*	−0.050*	−0.087**
	(1.348)	(0.019)	(0.019)	(0.022)	(0.024)	(0.027)
Discount rate (t-1)		0.994***	0.994***	0.994***	0.994***	0.991***
		(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
ER Short Target			−0.183	−0.181	−0.179	−0.322
			(0.342)	(0.371)	(0.336)	(0.349)
ER Long Target (1 year mov.av.)				−0.003		
				(0.158)		
ER Long Target (3 year mov.av.)					0.035	
					(0.087)	
ER Long Target (5 year mov.av.)						−0.204*
						(0.084)
Pre-election (Binary)	−0.031	0.065	0.065	0.065	0.066	0.062
	(0.609)	(0.055)	(0.055)	(0.055)	(0.056)	(0.055)
Post-election (Binary)	−0.052	0.009	0.010	0.010	0.010	0.007
	(0.605)	(0.014)	(0.014)	(0.015)	(0.014)	(0.016)
Constant	1.293	0.036*	0.040**	0.040*	0.036	0.059**
	(2.952)	(0.015)	(0.014)	(0.016)	(0.018)	(0.019)
Observations	307	307	307	307	307	307
Adj. R^2	0.004	0.992	0.992	0.992	0.992	0.992

Note: Newey West Standard Errors in Parenthesis. *p<0.05; **p<0.01; ***p<0.001.

Table A24: Linear Models - Discount Interest Rate (II)

	Dependent variable:					
	Change in the Discount Interest Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Polarity (t-1)	-0.050^{**}	-0.050^{**}	-0.053^{**}	-0.051^{*}	-0.047	-0.078^{**}
	(0.019)	(0.019)	(0.020)	(0.023)	(0.026)	(0.028)
ER Short Target			-0.151	-0.170	-0.147	-0.246
			(0.341)	(0.368)	(0.338)	(0.349)
ER Long Target (1 year mov.av.)				0.034		
				(0.150)		
ER Long Target (3 year mov.av.)					0.050	
					(0.089)	
ER Long Target (5 year mov.av.)						-0.162
						(0.083)
Pre-election (Binary)	0.066	0.066	0.066	0.066	0.066	0.064
	(0.054)	(0.054)	(0.055)	(0.055)	(0.055)	(0.053)
Post-election (Binary)	0.009	0.009	0.010	0.010	0.010	0.008
	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.016)
Constant	0.029	0.029	0.032	0.030	0.027	0.044
	(0.019)	(0.019)	(0.019)	(0.022)	(0.024)	(0.023)
Observations	307	307	307	307	307	307
Adj. R^2	0.047	0.047	0.047	0.047	0.048	0.058

Note: Newey West Standard Errors in Parenthesis. *p<0.05; **p<0.01; ***p<0.001.

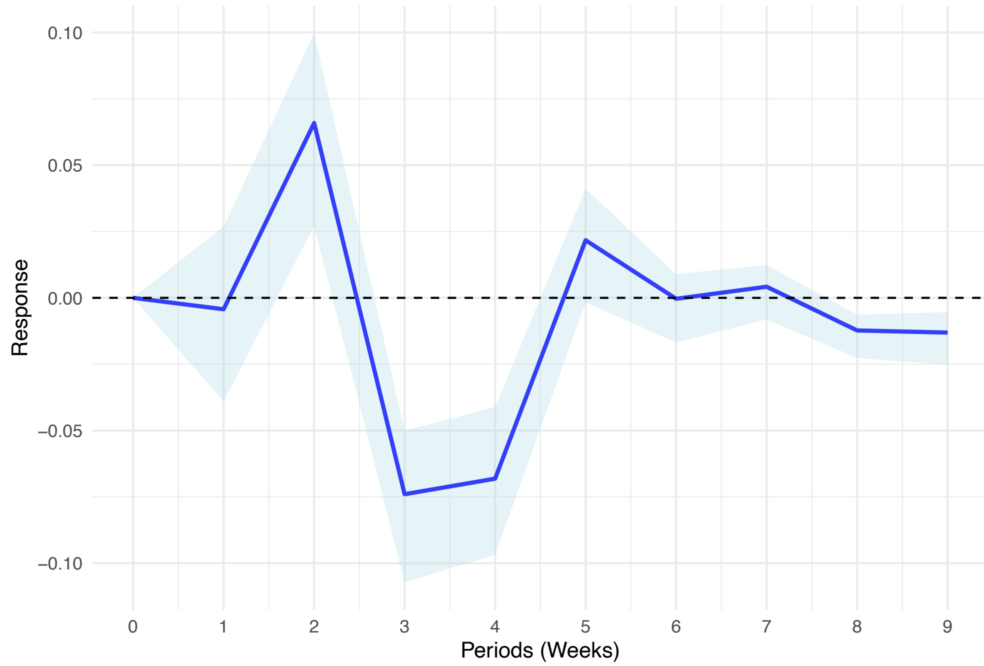
A.10 Nominal Exchange Rates and Industry Pressure in Japan and Korea

Finally, we also perform analogous tests on Japanese and Korean data using the effect of our polarity measure on the exchange rate itself. For Korea, we use news articles from the Korean *Hankyung* over the period 1994-2021. Unfortunately, we do not have official foreign exchange rate intervention data available in the case of Korea. Doing so requires changing the temporal structure of the model. The full causal chain linking industry lobbying to exchange rate depreciation via foreign exchange interventions seems unlikely to unfold within one day. As such, we run the analysis at the weekly level.

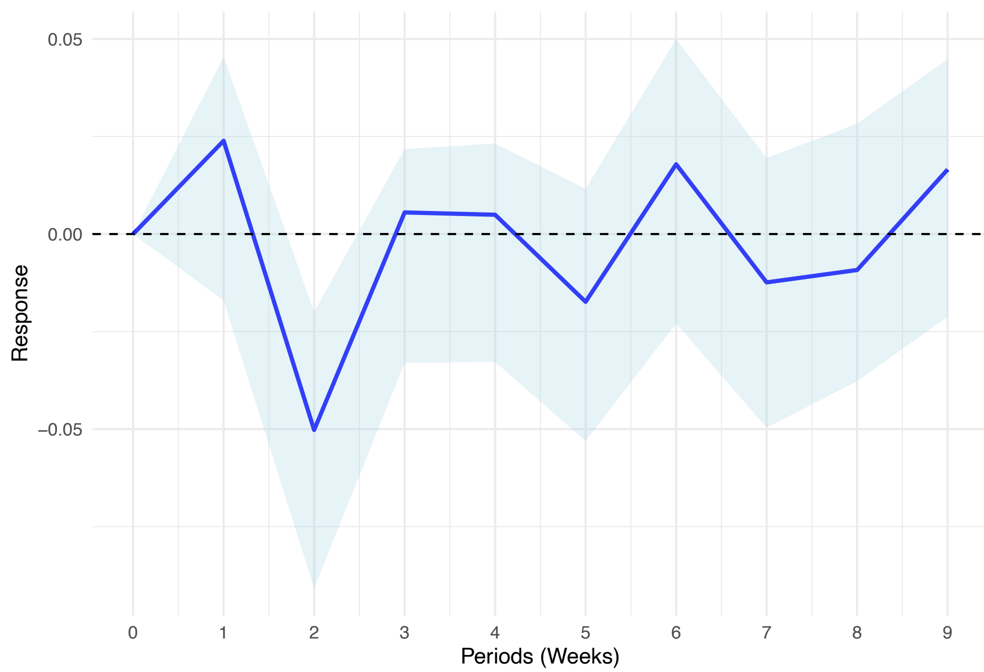
We can test how our polarity measure is related to the nominal exchange rate in a dynamic system with multiple time-series variables. By modeling the over-time interdependency of the variables, we track how shocks propagate through the system. Doing so is particularly advantageous in the case of Japan, for which we have the official intervention variable. Modeling the nominal exchange rate as a function of the central bank intervention (among other factors) creates feedback loops (e.g., the policy changes affect the markets and the markets affect the policy decisions). For this reason, the literature on the effect of foreign exchange intervention on the exchange rates often relies on Vector Autoregressions (VAR) or Local Projections (e.g., Menkhoff, Rieth, and Stöhr 2021). We follow this lead and estimate a set of VAR models focusing on how a shock to our polarity measure propagates through the system and affects the exchange rate.

We include three endogenous variables: intervention (ordered categorical), polarity, and the nominal exchange rate. As in the previous section, the exchange rate is coded such that a shock in the negative direction captures depreciation. In the case of Korea, we do not have the official intervention data, so it is a bivariate system. The optimal lag length is chosen according to the information criteria (allowing for a maximum of fifty lags), indicating five for Japan and twenty-three for Korea. We run unit root tests to assess stationarity. The nominal exchange rate is the only non-stationary variable, so that we use the first difference of the logged exchange rate as an approximation of the exchange rate growth (the replication package shows substantively identical results if we use the actual growth rate). Each system of equations also includes three exogenous regressors that can affect the endogenous variables contemporaneously: The pre- and post-election dummies and the long target. We include the long target, but not the medium target as the former is more likely to be exogenous. We show the results for the long target based on one year (52 weeks), but the conclusions remain the same if we use the long targets based on 3 or 5 years (available in the replication package). After fitting the reduced-form model, we test to ensure that the residuals are white noise. We rely on both the Ljung-Box and Breusch-Godfrey test and vary the lag length of the tests three times. We do not detect any autocorrelation in the residuals according to at least five tests out of six across all models mentioned in this section.

Below, we show the orthogonalized impulse response functions with 68% error bars based on bootstrapped standard errors (100 repetitions). We rely on the standard Cholesky decomposition to identify the shocks. As such, the ordering of the variables matters. Luckily, our theory has a relatively straightforward implication: we expect lobbying pressure to affect the central bank intervention first, and only later the exchange rate, so the polarity measure can affect intervention and the exchange rate only with a lag, but not contemporaneously. At the same time, a vast literature in international economics (Menkhoff, Rieth, and Stöhr 2021) suggests that while exchange rate movements do not affect central bank intervention immediately (since monetary authorities are more concerned with the longer-term trajectory of the exchange rate, which is the reason why we have included these terms in all our models), central bank interventions do affect exchange rate contemporaneously (at times, only within the very day of the intervention). Hence, the intervention variable is ordered first, followed by the nominal exchange rate and, finally, our polarity measure. Of course, in the case of Korea we have only the nominal exchange rate followed by our polarity measure. The orthogonalized IRF graphs in figure A6 below show how a one-standard deviation shock to our polarity score affects the exchange rate over time in Japan and Korea, respectively. They are based on the VAR(5) and VAR(23) including both a constant and a trend. Results omitting the trend are virtually identical and available in the replication package).



(a) Japan



(b) Korea

Figure A6: Orthogonalized IRFs

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