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Exchange Rate Pass-through after a Large Depreciation

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Abstract

This paper uses monthly scanner consumer price data to study exchange rate pass-through (ERPT) after the Kazakh Tenge switched from a fixed to a floating exchange rate regime in August 2015. The depreciation of the Tenge was large (50%), triggered overnight and unanticipated. This exchange rate shock allows us to have a clear identification strategy. In particular, we model ERPT to consumer prices using Local Projections estimations, which is especially well-suited to capture price dynamics after large shocks. We find that prices respond fast, yet incomplete. After 12 months the ERPT into consumer prices is between 25% and 34%. We also find that ERPT depends on the type of product, i.e. whether it is foreign sourced and whether the product is part of an international brand.

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1 Introduction

How do prices respond to exchange rate shocks? Recent depreciation episodes in both developed and emerging economies, like the UK, Turkey and Argentina, have shown that inflation only partially responds to exchange rate changes. There is a large literature discussing why exchange rate pass-through (ERPT) is incomplete (Krugman (1986) and Campa and Goldberg (2005)). In particular, Gopinath and Rigobon (2008) argue that in the short run, ERPT is determined by sticky prices and endogenous currency choice. Similarly, Gopinath and Itskhoki (2010) show that incomplete ERPT is driven by firm level variables such as firm-level markup variability (Amiti, Itskhoki, and Konings (2019)) and the extent to which firms internationally source intermediate inputs (Amiti, Itskhoki, and Konings (2014)). Moreover, heterogeneity in firm-level markup elasticities and intermediate input sourcing explain cross-sectional dispersion in currency choice (Gopinath, Itskhoki, and Rigobon (2010)), implying that short and long run ERPT are intimately related.

Initially, the empirical ERPT literature focused on modest movements of exchange rates in developed economies assuming that exchange rate shocks are orthogonal to firms' pricing decisions. For instance, Gopinath and Itskhoki (2010) and Berman, Martin, and Mayer (2012) use this assumption to provide evidence that pass-through into border prices is incomplete for US imports and French exports. However, to study the causal effect between currency shocks and consumer prices, it is important to clearly identify an exogenous shock in exchange rates that is rarely observed in the context of developed economies. While more recent literature study ERPT in the aftermath of economic crises in Brazil and Argentina, they do not identify the underlying cause of the associated currencies depreciations (e.g. Chatterjee, Rafael, and Vichyanond (2013) and Chen and Juvenal (2016). In contrast, this paper uses the switch from a fixed exchange rate to a floating exchange rate regime in Kazakhstan after the global commodity slump in 2015. This switch resulted in a depreciation of the Kazakh Tenge of almost 50% on an annual base relative to its main trading partners whereas the CPI only rose a little under 20%. Thus, this episode of depreciation allows us to identify an exogenous shock in exchange rates and study its impact on consumer prices.

The literature that studies how exchange rate fluctuations affect consumer prices in developing countries has relied mostly on aggregate price data (Burstein, Eichenbaum, and Rebelo (2005), Kraay (2007) and Campa and Goldberg (2010)). Like Antoniades and Zaniboni (2016) for consumer prices in the United Arab Emirates, we use micro level price data. Apart from the evident gains in estimation efficiency, micro-level data allows us to exploit the inherently heterogenous response of different types of products. To do so, we use monthly scanner data of 4,863 different products obtained from AC Nielsen Kazakhstan. The data cover various types of retail stores, from large supermarkets to small local shops that are spread over six major urban areas in Kazakhstan. The data span from January 2014 to December 2016, thus allowing to capture consumer prices well before and after the large depreciation of the Kazakh Tenge that took place in August 2015. We obtain the trade weighted exchange rates by matching each scanner product code to its 6-digit HS product code. This allows us to identify the major import partners for each product category.

Methodologically, we make use of Local Projections to construct dynamic multiplier functions (Jordà (2005)). An important advantage of local projections is that they relax implicit assumptions typically made in distributed lag models used in most papers. First, typically after a devaluation or large depreciation exchange rate changes may be serially correlated (Burstein et al. (2005)). Indeed, we use Monte Carlo simulations to show that Local Projections are robust to the presence of serial correlation while distributed lag models might fail to consistently recover the true parameter estimates. Second, Local Projections, compared to distributed lag models, are more flexible in controlling for past economic information, like the presence of a high inflation environment. Overall, our empirical strategy guards us against these confounding factors and to correctly study the ERPT into consumer prices after a large exchange rate shock.

Our study adds to the literature on price responses after a large devaluation (Burstein et al. (2005)) in the following ways. First, to date, empirical work has mainly focused on the cross-sectional heterogeneity in ERPT (see Berman et al. (2012), Chen and Juvenal (2016) and Corsetti, Crowley, Han, and Song (2018)) and has disregarded the dynamic effects of currency shocks. While some studies (e.g. Campa and Goldberg (2005), Gopinath and Rigobon (2008) and Bonadio, Fisher, and Sauré (2018)) have investigated the timing of ERPT for import prices, the pass-through into import prices may be quite different from pass-through into consumer prices due to distribution costs or different pricing strategies of supermarkets. This is important as the ERPT into consumer prices can provide a detailed picture on the distributional impact on consumer welfare (Cravino and Levchenko (2017)) and can help guide macroeconomic stabilization policies such as inflation targeting.

We further extend the literature by examining the effects of a large depreciations in the context of an emerging economy with a weak currency. To date, research has provided a vast amount of evidence on ERPT in developed economies characterized by the presence of strong currencies (mostly the USD). However, Gopinath (2015) and Maggiori, Neiman, and Schreger (2018) show that the US dollar is used as the main currency to invoice international trade transactions and to denominate international asset positions. Thus, the strength of the US dollar induces asymmetries to the extent to which international shocks are transmitted in the US economy compared to other economies without strong currencies (see Gopinath (2015) and Boz, Gopinath, and Plagborg-Møller (2017)). This implies that, while ERPT into U.S. consumer prices may be low, the reaction of consumer prices to an exchange rate shock in an economy without a strong currency (i.e. Kazakhstan) should be much higher. This is because, on the one hand, given that intermediate inputs and finished products exported to Kazakhstan are unlikely to be invoiced in local currency, it follows that short run and long run ERPT into consumer prices will be higher compared to the US. This is further echoed in Gopinath et al. (2010) who demonstrate that firms choose their preferred currency of invoicing in concordance with their desired level of long run ERPT. On the other hand, the high inflation environment of Kazakhstan implies that prices should be more responsive to external shocks. For example, Devereux, Engel, and Storgaard (2004) theoretically show that countries with a more stable macroeconomic environment tend to have lower exchange rate pass-through. Moreover, Alvarez, Lippi, and Passadore (2016) show that in state-dependent models of price adjustment exchange rate pass-through is quicker and faster when the size of the shock increases. By studying aggregate ERPT across a panel of 23 countries, Campa and Goldberg (2005) confirm this conjecture empirically. As we study the adjustment of prices in a setting of an emerging economy to a large currency depreciation, we are well positioned to validate these earlier papers.

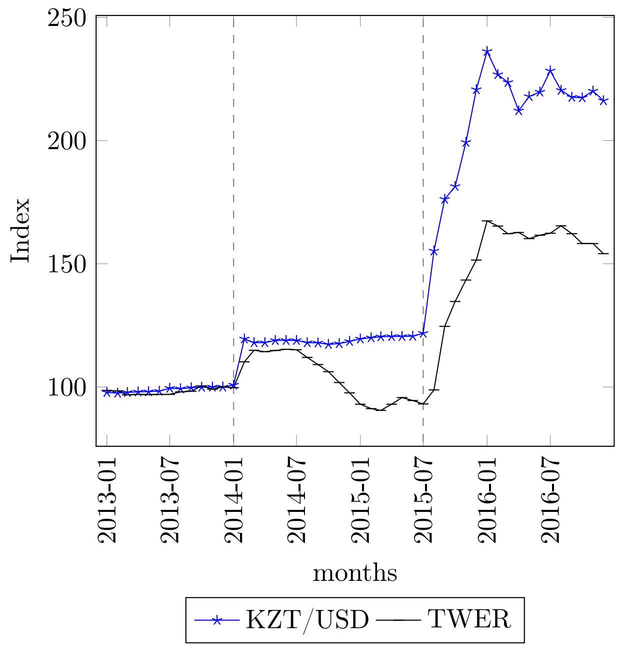
Our results show that consumer prices positively and instantaneously react to the exchange rate shock and that on average 25% to 34% of the exchange rate adjustment is passed-through into prices after 12 months. We find a reaction of consumer prices on impact and we document that the exchange rate pass-through after twelve months already materializes after six to nine months. In addition, we show preliminary evidence that, in line with Gopinath (2015), cross-country differences in the currency of invoicing could be one explanation for observed higher ERPT into consumer prices. In addition, we show that there is cross-sectional heterogeneity in the ERPT across products and firms. In particular, we show that the ERPT into consumer prices is higher for externally sourced goods compared to domestically sourced goods and that ERPT is lower for products, which are part of an international brand compared to products which are part of a local brand.

The rest of this paper is structured as follows. Section 2 provides background and context about the depreciation. Section 3 describes the use of Local Projection and provides the identifying assumptions for our setting. Section 4 describes the data. Sections 5 and 6 provide the results and the concluding remarks.

2 Context of the depreciation

On September 2^{nd}, 2013 the Kazakh National Bank moved from a managed floating exchange rate to a fixed exchange rate regime in which the Kazakh Tenge was pegged to a basket of currencies, including the US Dollar, Russian Ruble and the Euro. However, on February 11^{th}, 2014 the monetary authority depreciated the Tenge against this basket of currencies by 19%, which is illustrated by Figure 1. According to the official statement of the Kazakh National Bank, the devaluation was mainly induced by the decision of the Russian monetary authorities to allow the Ruble to float more freely to the US Dollar. In turn, the central bank decided to adjust its fixed exchange rate with the US Dollar "to take out the wind of the sails of speculators".[1] Still, the National Bank did signal that the central bank would be committed to obtain a relatively strict float around 185 KZT/USD. Again, 1 indicates that this objective was indeed successfully implemented until August 2015.

Figure 1: KZT/USD and KZT trade-weighted exchange rate



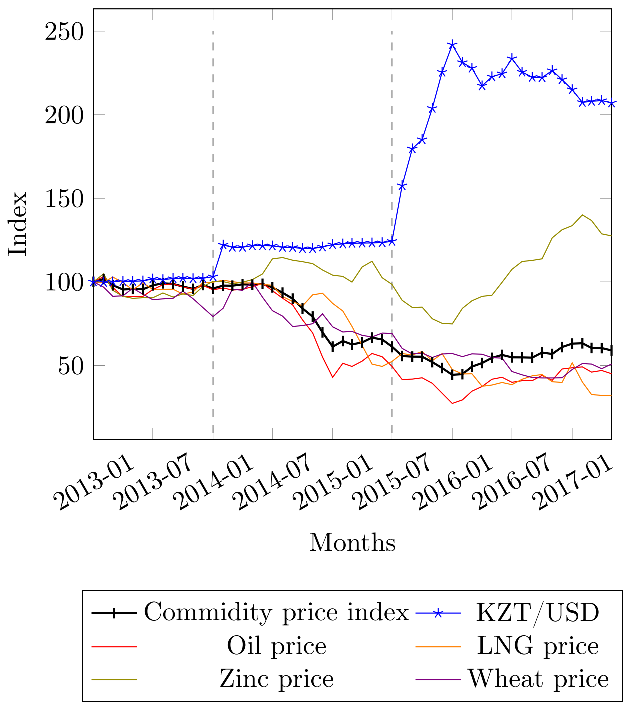
Notes: This figure shows the evolution of the KZT/USD and the trade-weighted exchange rate or effective exchange rate of KZT. The devaluations of February 2014 and August 2015 are both indicated with grey dashed lines. All data series are index with respect to January 2013 to make their evolutions comparable. The data is taken from Thomson Reuters EIKON and the National Bank of Kazakhstan.

On August 20^{th}, 2015, the central bank decided to discontinue its fixed exchange rate policy and shift its focus to inflation targeting. The main reason behind this decision was the continuing slide

[1] Kazakhstan devalues Tenge by 19 percent to stymie speculators. (Feb 11^{th}, 2014). *Reuters.* retrieved from https://www.reuters.com/article/kazakhstan-tenge/update-3-kazakhstan-devalues-tenge-by-19-percent-to-stymie-speculators-idUSL5N0LG07F20140211.

in global commodity prices that started in the second half of 2014. Figure 2 shows the prices of the six main commodities exported by Kazakhstan. This figure indicates that the commodity crisis preceded the depreciation of 2015 and was substantial given that some commodity prices fell by almost 50%. Table C.1 indicates that over 80% of Kazakhstan's goods exports are affected by these prices. For this reason, the Kazakh Central Bank chose to improve the country's competitiveness on international commodity markets and to absorb these external shocks-through exchange rate adjustments.

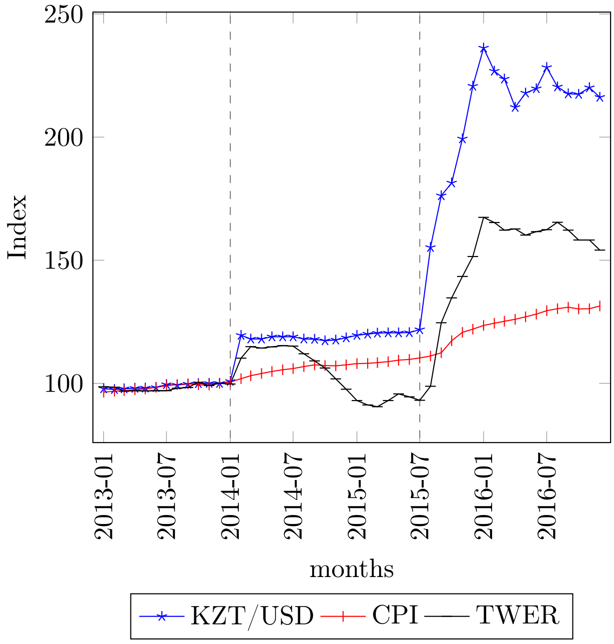
Figure 2: Commodity Prices



Notes: This figure depicts the global slowdown in commodity market prior to the depreciation of August 2015. We plot the USD/KZT exchange rate and the six main commodities exported by Kazakhstan which present over 80% of Kazakhstan's exports. All data series are index with respect to January 2013 to make their evolutions comparable. The data is taken from Thomson Reuters EIKON and the Federal Reserve Bank of St. Louis.

The magnitude and the nature of the Kazakh depreciation provides a unique opportunity to study the ERPT into consumer prices. First, the depreciation was large (see Figure 3). For example, just a couple of weeks after the government decided to switch to floating exchange rate regime, the Tenge had already depreciated by 27.7% vis-à-vis the US Dollar (as of August 20^{th}, 2015). Similarly, after one, three and six months, the currency had lost 36.9%, 55.9% and 78.5% of its value to the US Dollar, respectively. In sharp contrast to the literature that has mostly used modest currency fluctuations, Figure 3 shows that the exchange rate regime switch induced considerable variation in both exchange rates and inflation. This feature of our empirical setting allows us to clearly disentangle the effect of exchange rates on consumer prices.

Figure 3: KZT Devaluation episodes



Notes: This figure depicts the two devaluation episodes of February 2014 and August 2015 respectively. We show the reaction of the KZT/USD, the trade-weighted Kazakh Tenge index (TWER) and the domestic Kazakh Consumer Price index (CPI). All values are indexed with respect to December 2013. Data is taken from Thomson Reuters Datastream and the National Bank of Kazakhstan.

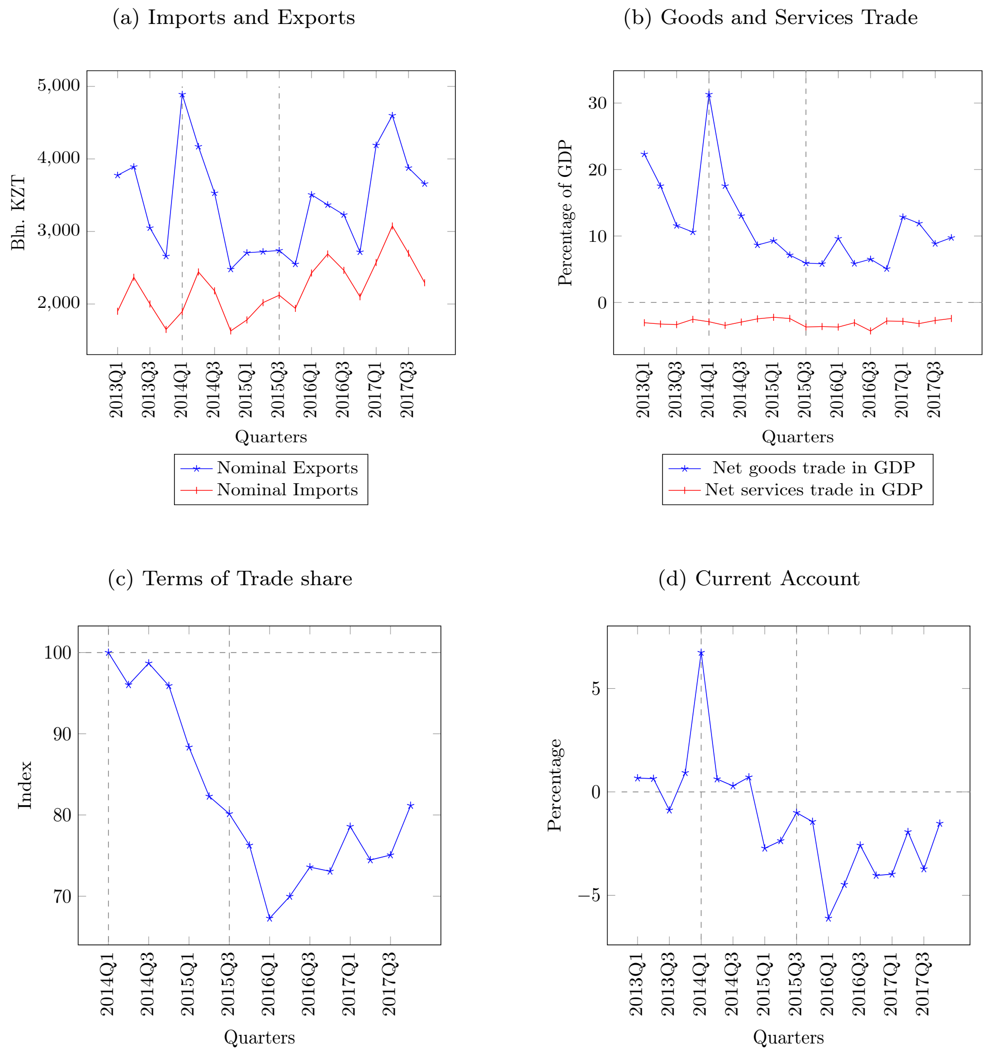
Second, we know that the depreciation was triggered by sliding oil and commodity prices as stated in the official communications of the Kazakh central bank. Consequently, this allows to control for any alternative causes that could have impacted consumer prices and the exchange rate. Similarly, given that the value of the KZT in the aftermath of the depreciation was mainly determined by financial markets, it is highly unlikely that firm-level pricing of non-durable consumer goods or (anticipated) firm-level productivity shocks were the driving forces behind these exchange rate fluctuations. Even though the deprecation was endogenous to the decisions of firms active in primary industries, it is exogenously given to the economic actors we consider.

Third, before the depreciation the Kazakh Tenge was a stable currency due to the managed float and the fixed exchange rate regime. Thus, the likelihood that price adjustment after the depreciation was caused by adjustment lags before the depreciation is minor (similar to Auer, Burstein, and Lein (2017)).

Fourth, given that the main macro-economic variables display a typical overvaluation-depreciation evolution, we are confident that the depreciation was the main economic shock driving our results. Unsurprisingly, the depreciation had an important effect on the import and export conditions for

Kazakhstan. Figure 4a shows nominal exports were going down significantly prior to the depreciation of 2015, which is line with sliding commodity prices prior to August 2015. Due to the limited reaction of imports, the share of net exports of goods in GDP dropped significantly. From Figure 4b, we infer that the net export of services did not react much and remained stable and negative. The current account turned negative subsequently.

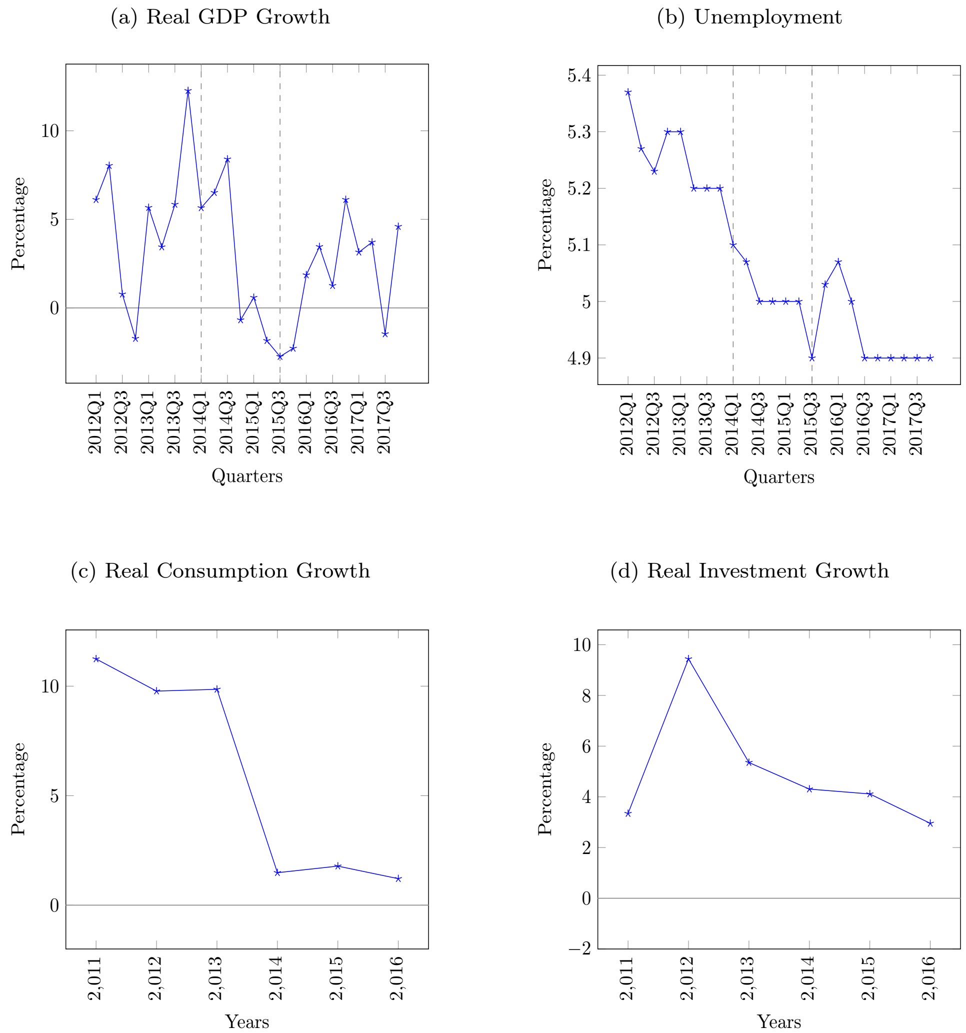
Figure 4: International Trade



Notes: We show the trajectory of the Kazakh economy before, during and after the depreciation episode. This figure is inspired on the work of Bonadio et al. (2018) who consider a similar setting for the Swiss depreciation of 2015. Data is taken from Thomson Reuters Datastream and the National Bank of Kazakhstan.

Still, Figure 5 shows that the large impact on the trade balance of Kazakhstan propagated into the real economy only to a limited degree. Real GDP had a temporarily negative reaction which turned positive after two quarters. The overall unemployment level saw only a very slight uptick and returned to previous levels within one year. Both real consumption and real investment did not seem to suffer from the depreciation. Altogether, the macroeconomic picture shows that the real economy dipped, but quickly recovered in response to the commodity price slump and the successive depreciation. The limited effect appears to have worked mainly through the trade balance and not due to a drop in real consumption expenditures. This picture together with the sheer size of the shock makes us confident that the estimated effects will be largely due to the depreciation and only to a limited degree to other potentially confounding factors.

Figure 5: Real Economy



Notes: We show the trajectory of the Kazakh economy before, during and after the depreciation episode. This figure is inspired on the work of Bonadio et al. (2018) who consider a similar setting for the Swiss depreciation of 2015. Real GDP growth is defined as real GDP relative to real GDP of the same quarter one year earlier. Real Consumption and Real Investment Growth are defined as year-on-year growth rates. Data is taken from Thomson Reuters Datastream and the National Bank of Kazakhstan.

3 Methodology

3.1 Empirical Framework

There is a growing literature that considers the pricing decision of firms as a dynamic process. Studies have shown that price dynamics are due to the presence of nominal rigidities in the adjustment of consumer prices (Klenow and Kryvtsov (2008) and Eichenbaum, Jaimovich, and Rebelo (2011)) and to the presence of strategic complementarities in price setting (Amiti et al. (2019)). Following recent developments in econometrics, we model these dynamic effects with Local Projections (developed in Jordà (2005)).[2] The Local Projections framework is suitable to estimate ERPT dynamically and, at the same time, relaxes certain implicit assumptions made when estimating ERPT using a distributed lag model. We start with a general framework that assumes the following form:

$$\Delta_h p_{i,t+h} = \beta^h \Delta er_{i,t} + \sum_{l=1}^{L} \gamma_l^h \Delta er_{i,t-l} + \sum_{l=0}^{L} \delta_l^h \Delta X_{i,t-l} + \varepsilon_{i,t+h} \qquad \text{with } h = 0, \cdots, H. \tag{1}$$

$p_{i,t}$ is the natural logarithm of the price of good i at time t and $\Delta_h p_{i,t+h} = p_{i,t+h} - p_{i,t-1}$. Further, $er_{i,t}$ is the logarithm of the nominal exchange rate and $\Delta er_{i,t}$ is the first difference of $er_{i,t}$ which is associated with a horizon varying coefficient, β^h, as we evaluate the specifications at different horizons $h = 1, \cdots, H$. We add L lags of Δer_{it} to control for serial correlation in the exchange rate change and the possibility that prices adjusted in response to an earlier exchange rate change. This is standard in the Local Projections literature.[3] $X_{i,t}$ is a vector of controls that enters in log-differences and of which we include L lags as controls as well. [4]

The Local Projections framework provides several advantages over other estimation techniques use in previous research (e.g. distributed lag models).[5] First, Local Projections allow for the presence of a dynamic structure in the independent variables which is an important feature of our data. In contrast, to Distributed Lag models, which estimate the effect of the independent variable

[2]Local Projections have been introduced as an alternative to VAR-specifications to obtain impulse response functions. One of the main advantages to VAR-specifications is that local projections can be estimated relatively easily by OLS and that they are more robust to misspecification of the data generating process. Notwithstanding these benefits, VAR-specifications are more efficient if the true data generating process is VAR.

[3]We omit the lag of the first difference of the left hand-side variable as a control variable in the baseline specification. This is because we do not apply this method to highly serially correlated aggregate data, but instead to high frequency micro price data. Given that monthly price data generally display a frequency of price adjustment above one month (Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008)), it is unlikely that the month-on-month price change will display a high degree of serial correlation. Nevertheless, our results are robust to the inclusion of a lagged dependent variable which we show in section 5.2.1.

[4]Given that the left-hand side variable is a cumulative difference, $\varepsilon_(i, t+h)$ is serially correlated by construction. Therefore, we estimate standard errors using the Driscoll and Kraay (1998) variance estimator such that the standard errors robust to heteroskedasticity, arbitrary forms of clustering and serial correlation up to some lag.

[5]A distributed lag model to dynamically estimate ERPT, assuming the number of lags included to be q, would be of the following form:

$$\Delta p_{i,t} = \sum_{l=0}^{q} \Delta er_{i,t-l} + \sum_{l=0}^{q} \Delta X_{i,t-l} + \varepsilon_{it}.$$

at a certain point in time keeping all its future values constant, Local Projections allow for the transmission of the effect of the independent variables on the dependent variable through the future values of the independent variables. In appendix A we show, using Monte Carlo simulations, that Local Projections recover the true dynamic multiplier and that a distributed lag model is unable to do so. Second, Local Projections allow to control for macroeconomic information, such as passed inflation, at time $t-1$. On the contrary, including inflation at time $t-1$ in a Distributed Lag model would shut down the transmission of exchange rate shocks at $t-l$ (with $l>1$) to consumer prices at t through aggregate inflation at $t-1$. Overall, previous research has overlooked these considerations due to its focus on moderate exchange rate fluctuations that are approximated by a white-noise process (Engel and West (2005)). However, as Figure 1 indicates, the depreciation of 2015 induced serial correlation in the exchange rate series even in first differences making the white-noise assumption untenable. Also, from 2014 to 2016 CPI inflation in Kazakhstan was consistently positive and high. For these two reasons, Local Projections are ideally suited for our and similar contexts.

3.2 Identification

We face three challenges when identifying the ERPT into consumer prices. First, given the size of the shock and the timespan we consider it is possible that the data is not stationary which could potentially lead to spurious regressions. Second, we need to assume that the shock is exogenously given to the economic actors in our data. Third, simply regressing prices on exchange rates could lead to an omitted variable bias. We next elaborate how we deal with these concerns.

Previous empirical evidence suggests that prices and exchange rates usually contain a unit root, but their first differences are typically stationary (Corbae and Ourialis (1988) and Engel and West (2005)). However, in our case, the extent of the exchange rate shock may have caused that even the first difference could have a unit root. Indeed, Table 1 shows that, in line with the literature, we are unable to reject the null hypothesis of a stochastic trend in the levels of the main variables of interest. When we apply the first difference operator, we reject the null hypothesis of the presence of a stochastic trend and find reassuring evidence that the first difference of the main variables of interest are stationary.[6]

[6] The stationarity tests for the panel variables allow for cross-sectional dependence. Table C.3 uses an augmented Dickey-Fuller to show that the main control variables, which are all time series variables, are also stationary.

Table 1: Panel unit root Test

Variable	*No trend*			*Trend*		
	1 lag	*2 lags*	*3 lags*	*1 lag*	*2 lags*	*3 lags*
Levels						
Exchange rate	(-1.91)	(-1.41)	(-1.47)	(-2.68)	(-2.30)	(-2.46)
Labour cost	(-3.26)*	(-2.83)	(-2.22)	(-3.45)	(-3.04)	(-2.27)
Product price	(-2.44)	(-2.13)	(-1.99)	(-3.10)	(-2.77)	(-2.61)
Log differences						
Exchange rate	(-4.97)***	(-3.69)**	(-3.37)**			
Labour cost	(-5.25)***	(-4.52)***	(-3.87)**			
Product price	(-4.31)***	(-3.53)**	(-3.10)*			

Notes: This table presents the panel unit root tests for the trade-weighted exchange rate, the trade-weighted labour unit cost index and the product prices. We use the panel unit root test proposed by Pesaran (2007) which is robust to cross-sectional dependence and where we allow for different forms of autocorrelation in the residuals. The maximal number of lags is chosen in accordance to Newey and West (1987) rule of thumb which implies $\text{Lag}_{max} = \sqrt[4]{T}$. For the variables in levels we ran a test with a constant and no trend and a test with both a constant and a trend, for the log differences we only included a constant. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

Second, in order to establish causal evidence of EPRT into consumer prices, the key assumption is that the exchange rate shock is exogenous. In other words, we need to assume that companies cannot affect the exchange rates. The official statement of the Kazakh National bank on August 21^{th} indicated that the regime change was induced by ongoing downward pressure on global commodity prices. Thus, it becomes very plausible that the exchange rate shock was caused by external forces (i.e. the overnight decision of the Kazakhstan national bank) and not by the actions of firms producing grocery products.

Third, our identification strategy allows us to guard against omitted variable bias identified in previous research on ERPT (Engel and West (2005), Nakamura and Zerom (2010) and Enders, Müller, and Scholl (2011)). Nakamura and Zerom (2010)[7] point to the possibility that oil prices drive the changes in both goods prices and exchange rates. Similarly, Engel and West (2005) and Enders et al. (2011) look at how contemporaneous or anticipated productivity shocks may drive real exchange rates and hence nominal exchange rates. As already mentioned in section 2, our specific setting provides arguments against the presence of an omitted variable. However, considering that oil price fluctuations led to the currency shock, it becomes highly unlikely that contemporaneous and anticipated productivity shocks drove the real exchange rate. Instead, we do include current and lagged commodity prices to control for the downward pressure on commodity

[7] Nakamura and Zerom (2010) study ERPT in the coffee market attributing variation induced the prices of coffee at the wholesale and retail level to weather shocks.

that lead to the devaluation. Also, we include past inflation as a control variable to control for any price change that is the result of past inflationary shocks that might be correlated with the exchange rate changes. Additionally, by controlling for labor costs in the countries of origin we try to control for such correlation still left in the data.

4 Data

To estimate exchange rate pass-through into consumer prices, we combine three datasets to obtain a panel at monthly frequency spanning the period from January 2014 until December 2016. The consumer price data is obtained from AC Nielsen Kazakhstan. Information on bilateral exchange rates and macroeconomic control variables, such as global oil and commodity prices and domestic inflation, is obtained from the Thomson Reuters EIKON platform. We consulted The UN Comtrade database to collect monthly data on imports into Kazakhstan of the different products in the sample.

Table 2 provides an overview of the dataset. The consumer price data covers 4,863 different products going from food products, such as milk and snacks, to personal care items like diapers and tooth paste. AC Nielsen Kazakhstan gathered the consumer price data across 6 urban regions: Astana, Almaty, Shymkent, Karanganda, Pavlodar and Ust-Kamenogorsk. Since all products are observed across 28 types of stores, including large supermarkets and open market venues, we define a cross sectional observation as a product that is observed in a store type in a certain month. This provides us with a total of 15,815 cross-sectional observations as not all products are observed in all different stores.

Table 2: Data overview

Frequency	*All*	*Monthly*	*Bimonthly*
Observations	376,182	183,024	193,158
Product cat.	64	23	41
Products	4,863	1,532	3,331
Store types	28	23	19
Cross Section	15,815	5,084	10,731

Notes: This table gives an overview of the dataset. For the whole dataset and the subsamples observed on a monthly and bimonthly basis we denote the total number of observations, the number of product categories, products and store types in which they are observed.

Our rich dataset provides an extensive geographical coverage of retail stores in Kazakhstan as well as contains a large set of consumer products and presents the following characteristics. First, we observe aggregate-level prices across outlets of the same store type. For instance, the product "Colgate Gentle Whitening Fluorca 50ml" is observed in the store type "Super/Large Mixed Supermarkets" and its associated price is an average taken across different outlets of this store type. Given that outlets of the same store type may adhere to different supermarket chains and prices of the same product may differ across supermarket chains, price changes may originate from two sources. The price may change because the underlying prices across outlets of the same store type change or because the market share distribution over the outlets changes. While this limits our ability to study the frequency of price changes in response to exchange rate shocks, it still allows us to obtain the timing and the effects of ERPT into consumer prices in a wide variety of categories. Second, we consider only those products that are observed at the monthly level to ensure consistency in our results (see table 2). Third, to match each product and the appropriate exchange rate, we construct a trade-weighted exchange rate per product category.[8][9] In this way, each product in a product category is subject to the same trade-weighted exchange rate, er_{it} for a product observed in a store i in time t is an index number which is calculated in the following way:

$$er_{it} = 100 * \prod_{a=1}^{A} [\frac{er_{at}}{er_{a0}}]^{w_{iat}} \tag{2}$$

In equation 2 er_{at} and er_{a0} are the bilateral exchange rate of country a with respect to Kazakhstan at time t and 0 respectively. The set $\{1, \ldots, A\}$ includes the 50 countries from which Kazakhstan imports the most.[10] The variable w_{iat} is the trade weight that is calculated as the ratio of the imported value of product i from country a at time t to the total imported trade value of product i at time t.[11] Recent work by Amiti, Itskhoki, and Konings (2018) and Chen, Chung, and Novy (2018) argues that matching the product with the appropriate currency is essential to estimate exchange rate pass-through. However, as the policy change caused a synchronized fall of the Tenge across all currencies of its trade partners and Russia is the source country for over 60% of Kazakhstan's imports, we believe that the trade-weighted exchange rates are a good proxy for the relevant exchange rates.

Finally, we construct a trade-weighted labor unit cost index in a similar way to the trade-weighted exchange rates and obtain a product category-specific control for labor unit costs.

[8] Generally, ERPT is only estimated for imported goods. In the presence of strategic complementarities in pricing and the use of internationally sourced intermediate, there will be an effect of the exchange rate on domestically produced goods as well. Since we do not distinguish between foreign and domestic goods, our estimates will be a weigthed average of the ERPT into both groups. In section 5.2.2 we do classify goods as being local and foreign and shows that foreign goods not-affiliated to an international group have higher pass-through

[9] The product categories in the dataset do not correspond one to one with the Harmonzied System codes we use to infer the most important trade parterns for each product category. For this reason, we constructed a correspondance table between the product codes in the dataset and the Harmonized System codes at the 6 Digit level. This table correspondance can be found in Table C.18.

[10] The total trade value of goods imported from these countries represents a little over 98% of the total trade value imported by Kazakhstan in 2015. We assume that this set of trade partners is the same in 2014 and 2016 as well.

[11] At the time of writing, the monthly trade data was not yet available for the year 2016. For this reason, we calculate the trade weight for 2016 as the average trade weight of 2014 and 2015. However, since there are very persistent patterns in the trade shares for different partners across all product categories, we consider this as a very mild practical assumption.

5 Results

5.1 Overall results

From Table 3, which uses the monthly sample to estimate equation 1[12], and from Figure 6, which presents the results graphically, we draw three important conclusions.[13].

First, the results indicate that the reaction of consumer prices to the exchange rate shock is instantaneous. In all specifications we observe that the coefficient at $h = 0$ is positive and significant though small in size. Due to the limited evidence on short run ERPT into consumer prices, we compare our results with evidence on border or import prices. This result is in line with the results in Bonadio et al. (2018) who find significantly negative effects of Swiss Franc appreciation in 2015 on border prices that materialized within the first month after the shock.

Second, Figure 6 shows that the maximum level of price adjustment is reached after six to nine months and remains stable for the rest of horizon. This echoes the findings that, due to the presence of inventories of intermediate goods and of finished goods at the level of the retail sector, border prices are relatively fast to adjust. For example, Bonadio et al. (2018) identify that the price adjustment process of import prices is already completed within one to two months after the appreciation of the Swiss Franc. In turn, if inventories function as a buffer to shocks, as in Blinder (1986) and Alessandria, Kaboski, and Midrigan (2010), the price adjustment from border prices into consumer prices will take time and reconciles our findings with the findings of Blinder (1986) and Alessandria et al. (2010). While Gopinath and Itskhoki (2010) show that it takes two years for US import prices to fully adjust to exchange rate fluctuations, their findings can be explained by the dominance of the USD in international trade transactions. Indeed, Gopinath and Rigobon (2008) argue that the USD is the main currency of invoicing for US imports and that these import prices are sticky in their currency of invoicing leading to slow EPRT into US import prices. Furthermore, Gopinath (2015) and Boz et al. (2017) provide evidence that prices of internationally traded goods between over 2,500 country pairs are sticky in USD. In turn, Boz et al. (2018) develop a general equilibrium model in which prices are set in USD and show that fast ERPT into prices is observed in countries that see their currency depreciate with respect to the US dollar.

Third, the level of exchange rate pass-through after twelve months is between 25% and 34%. We find higher pass-through compared to Hellerstein (2008) who finds that exchange rate pass-through is between 7% and 9% using monthly consumer prices for the US beer market. Also, our results

[12] We do not include seasonal dummies since the dependent variable is a cumulative price change and not a period-on-period one. Given that seasonal effects are mean zero over the whole period, they will not affect the cumulative effects on longer horizons. Still, they may affect the short-run estimates. However, when including seasonal effects the short-run coefficients are very close to the ones that are reported.

[13] We include four, five and six lags of the control variables. We choose to include a minimum of four lags of the control variables as Klenow and Kryvtsov (2008) have a lower bound of four months on their frequency of price adjustment of consumer prices. Hence, we need to control for at least four months of past information. We include a maximum of six lags of control variable as the inclusion of more control variables lead to issues of multicollineairity. These results are robust to changing the number of control variables included in the specification. Tables C.6 - C.8 show the estimated coefficients for all lag specifications and all horizons.

are close to the results of Gopinath and Itskhoki (2010) for US import prices. For differentiated goods, they find exchange rate pass- through after two years to be around 35%. Given that this result is obtained for import prices, the eventual exchange rate pass-through into consumer prices would have been considerably lower due to the presence of local non-traded costs at the level of the distribution sector. In addition, Antoniades and Zaniboni (2016) find pass-through after 12 months to around 20% which is a lower bound on our results. Indeed, our results are in line with the earlier results of Burstein et al. (2005) who study five depreciation episodes in emerging economies[14] in the 1990s and 2000s and report considerable price adjustment of consumer prices. For instance, for Argentina they document that the year-on- year cumulative change of the CPI was around 34% in 2002, whereas the trade-weighted exchange rate depreciated by 110%. Hence, our results using micro data are very close to their results using aggregate price indices (25-34% versus 31% for Burstein et al. (2005)).

Overall, our results indicate that exchange rate pass-through into consumer prices was considerably faster and higher compared to the evidence for the US. We believe that the strength of the US Dollar and the nature of the shock are important reasons for these findings. The results are consistent with Gopinath (2015) and Boz et al. (2017) who show that the omnipresence of the USD in international trade transactions induces faster and higher adjustment of import price of final goods and intermediate inputs. Further, according to Alvarez et al. (2016) and Bonadio et al. (2018) the large and permanent depreciation of the Kazakh Tenge might have induced higher and quicker adjustment. Alvarez et al. (2016) show that size and speed of exchange rate pass-through increases with the size of the shock which they rationalize this finding theoretically in a state-dependent price setting environment.

[14] The following depreciation episodes were studied: Mexico (1994), Korea (1997), Brazil (1997), Thailand (1997) and Argentina (2002)

Table 3: Baseline results

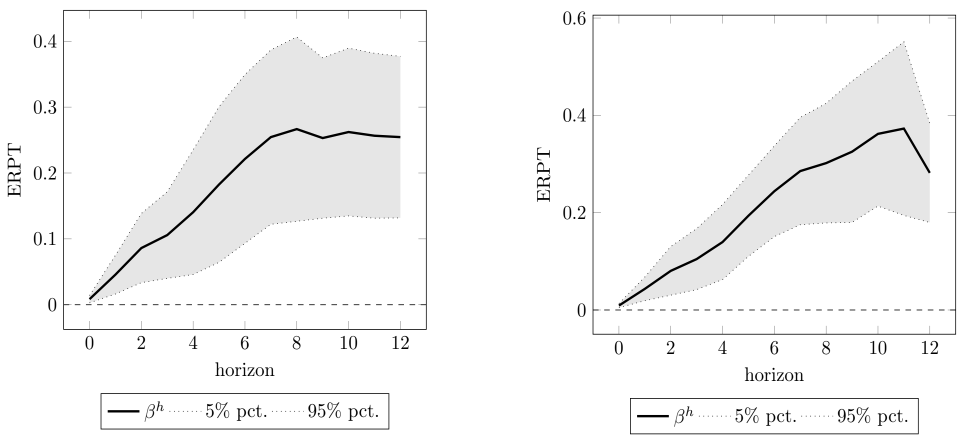
Horizon	$\hat{\beta}^h$	*p-value*	$5\% - CI$	$95\% - CI$	N	R^2
L = 4						
h = 0	0.008***	0.0041	0.00290	0.01397	122,822	0.057
h = 6	0.221***	0.0016	0.09320	0.34949	94,307	0.319
h = 12	0.254***	0.0004	0.13185	0.37707	68,741	0.400
L = 5						
h = 0	0.008***	0.0007	0.00374	0.01245	119,623	0.058
h = 6	0.223***	0.0000	0.13547	0.31025	91,151	0.335
h = 12	0.340***	0.0000	0.21811	0.46120	65,594	0.440
L = 6						
h = 0	0.009***	0.0001	0.00483	0.01332	116,368	0.060
h = 6	0.244***	0.0000	0.15079	0.33736	87,934	0.347
h = 12	0.282***	0.0000	0.17988	0.38372	62,382	0.504

Notes: This table presents the results at horizon 0, 6 and 12 after estimating equation 1 using the monthly sample and while including either 4, 5 or 6 lags of the control variables. We calculate standard erros based on the Driscoll and Kraay (1998) variance estimator. In this way we correct the standard errors for the presence conditional heteroskedasticity, aribtrary spatial correlation and autocorrelation. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

Figure 6: Impulse response function: Baseline Regression

(a) Using four lags

(b) Using six lags



Notes: Here we present the results of table 3 graphically. We present the coefficient estimate β^h $\forall h = 1, \cdots, 12$ and the 95% confidence intervals which are calculated using the Driscoll and Kraay (1998) variance estimator. The left panel presents these results for the case where we include into 4 lags of control variables. This right panel does for up to 6 six lags.

5.2 Robustness

5.2.1 Dynamic Specification

One potential concern regarding our modelling approach is that the omission of a lagged dependent variable may lead to biased estimates. In particular, the coefficient on the exchange rate change could suffer from an upward bias if a part of the cumulative price change is attributed falsely to the exchange rate shock whereas it in fact is due to staggered price adjustment that induces serial correlation the price change. In order to deal with this potential concern, we re-estimate the price response to the exchange rate change while including the lag of the month-on-month price change as a control variable. This leads to the following expression:

$$\Delta_h p_{i,t+h} = \beta_1^h \Delta er_{i,t} + \beta_2^h \Delta p_{i,t-1} + \sum_{l=1}^{L} \gamma_l^h \Delta er_{i,t-l} + \sum_{l=0}^{L} \delta_l^h \Delta X_{i,t-l} + \varepsilon_{i,t+h} \qquad \text{with } h = 0, \cdots, H. \tag{3}$$

where the coefficient β_2^h captures the effect of a price change in the previous period on the cumulative change of the price at horizon h.[15]

In Table 4 and Figure 7 we show that the results of our main model are robust to the inclusion of the lagged dependent variable. Indeed, we find practically identical results when we look at Figure 7 that shows the results with and without inclusions of the lagged price change as a control. In addition, we find that the effect of the lagged price changes is negative (Table 4). We interpret this result in the light of the highly disaggregated and micro price dataset we use. In the presence of nominal rigidities, e.g. menu costs, individual consumer prices are generally characterized by a frequency of price adjustment between 4 and 9 months (Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008)). Because of this, it is very unlikely that prices change in subsequent periods which induces a negative correlation between a price change in the current and future periods. Altogether, we conclude that our results are robust to the inclusion of a lagged dependent variable.

[15] We estimate this regression using the OLS estimator. In this way, we acknowledge that the coefficient on lagged dependent variable is prone to the well-known Nickell (1981). Still, as the construction of the dynamic multiplier functions only depends on the coefficient β_1^h and that the correlation in the sample between the exchange rate change and the lagged price change is equal to

$$-0.01$$

, we do not consider this to be of great concern.

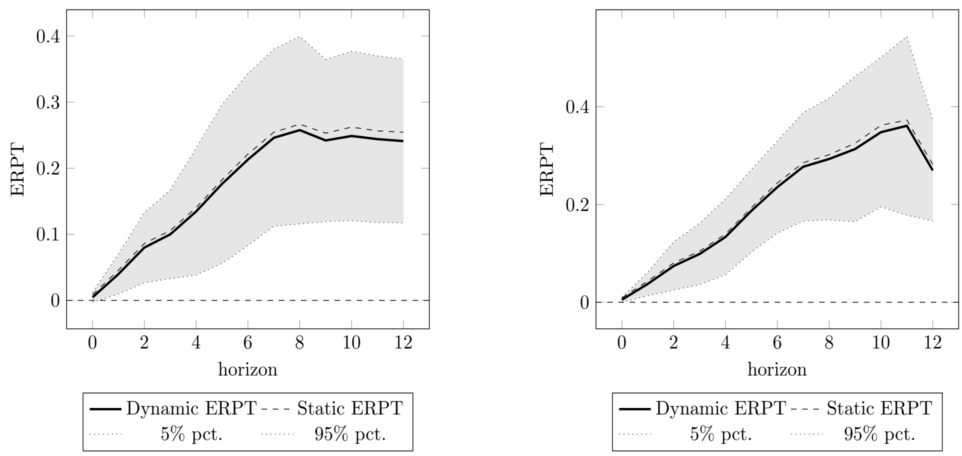
Table 4: Baseline results - Dynamic

Horizon	*Coef.*	$\hat{\beta}_i^h$	*p-value*	$5\% - CI$	$95\% - CI$	N	R^2
L = 4							
h = 0	i = i	0.005	0.2185	-0.00283	0.01189	120,675	0.077
	i = 2	-0.138***	0.0000	-0.16739	-0.10786		
h = 6	i = i	0.213***	0.0025	0.08300	0.34321	92,701	0.335
	i = 2	-0.271***	0.0000	-0.30740	-0.23505		
h = 12	i = i	0.241***	0.0007	0.11725	0.36488	67,434	0.411
	i = 2	-0.362***	0.0000	-0.43298	-0.29135		
L = 5							
h = 0	i = 1	0.004*	0.0999	-0.00083	0.00904	117,561	0.080
	i = 2	-0.139***	0.0000	-0.16752	-0.11041		
h = 6	i = 1	0.214***	0.0000	0.12572	0.30249	89,618	0.351
	i = 2	-0.275***	0.0000	-0.30903	-0.24149		
h = 12	i = 1	0.328***	0.0000	0.20244	0.45329	64,360	0.450
	i = 2	-0.336***	0.0000	-0.39515	-0.27663		
L = 6							
h = 0	i = 1	0.005**	0.0473	0.00007	0.01021	114,390	0.081
	i = 2	-0.139***	0.0000	-0.16793	-0.11039		
h = 6	i = 1	0.236***	0.0000	0.14145	0.32967	86,481	0.363
	i = 2	-0.277***	0.0000	-0.31204	-0.24247		
h = 12	i = 1	0.270***	0.0000	0.16643	0.37267	61,229	0.514
	i = 2	-0.322***	0.0000	-0.37031	-0.27375		

Notes: This table presents the results at horizon 0, 6 and 12 after estimating equation 3 using the monthly sample and while including either 4, 5 or 6 lags of the control variables. We calculate standard erros based on the Driscoll and Kraay (1998) variance estimator. In this way we correct the standard errors for the presence conditional heteroskedasticity, aribtrary spatial correlation and autocorrelation. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

Figure 7: Impulse response function: Baseline Regression - Dynamic

(a) Using four lags (b) Using six lags



Notes: Here we present the results of table 4 graphically. We present the coefficient estimate $\beta^h \quad \forall h = 1, \cdots, 12$ and the 95% confidence intervals which are calculated using the Driscoll and Kraay (1998) variance estimator. The left panel presents these results for the case where we include into 4 lags of control variables. This right panel does for up to 6 six lags.

5.2.2 Heterogeneity

To examine cross-sectional heterogeneity in ERPT, we subdivide the data into two mutually-exclusive groups.[16] First, we distinguish between international brands and local brands. International brands are defined as brands that are active not only in the Central Asian markets but are also active for example in Europe or on the American continent; Local brands are mainly active in Central Asia. Second, we categorize products into foreign products and local products. Local products are assumed to be only sold in Central Asian markets and foreign products are available to consumers globally. It is important to note that both categorizes do not perfectly overlap. To fix ideas, the product category Toothpastes provides an illuminating example. For instance, the international group Unilever has both so-called foreign ("Pepsodent ZashCariesSvYabl +50%Ca CA100m") and local products ("UNI LesnBalsam PriKrovotDesen Dub Z 75ml"). There are also foreign products such as the European "Lacalut White C 50ml" and local Central-Asian products like "Splat SplatProf WhitePlus WA 100ml" that cannot be linked to a large international brand.

To investigate this cross-sectional heterogeneity in ERPT along the two dimensions described in the previous paragraph, we consider two slightly altered versions of equation 1. First, equation 4 adds a term that interacts the exchange rate in first differences $\Delta er_{i,t}$ with a dummy variable d_i which is either 0 or 1 to study heterogeneity in ERPT along one dimension at a time[17]:

[16] We point out that the classifications are constructed by inspecting the data and classifying the products into these two groups by ourselves. For this reason, we acknowledge that the classifications may be susceptible to measurement error.

[17] $D_i = 1$ for international brand when we compare local and international brands and zero otherwise. When comparing the reaction of local and foreign goods, $D_i = 1$ for local goods and zero otherwise.

$$\Delta_h p_{i,t+h} = \beta^h \Delta er_{i,t} + \beta_2^h \Delta er_{i,t} * d_i + \sum_{l=1}^{L} \gamma_l^h \Delta er_{i,t-l} + \sum_{l=0}^{L} \delta_l^h \Delta X_{i,t-l} + \varepsilon_{i,t+h} \quad \text{with } h = 0, \cdots, H. \tag{4}$$

Hence, the coefficient associated with the interaction term, β_2, indicates the difference in ERPT from the base group ($d_i = 0$) for the observations that are part of the other group ($d_i = 1$). Second, equation 5 interacts the exchange rate in first differences $\Delta er_{i,t}$ with two dummies which allows us to study cross-sectional heterogeneity along two dimensions at the same time:

$$\Delta_h p_{i,t+h} = \beta_1^h \Delta er_{i,t} + \beta_2^h \Delta er_{i,t} * d_i^1 + \beta_3^h \Delta er_{i,t} * d_i^2 + \beta_4^h \Delta er_{i,t} * d_i^1 * d_i^2 + \sum_{l=0}^{L} \gamma_l^h \Delta X_{i,t-l} + \varepsilon_{i,t+h} \text{with } h = 0, \cdots, H. \tag{5}$$

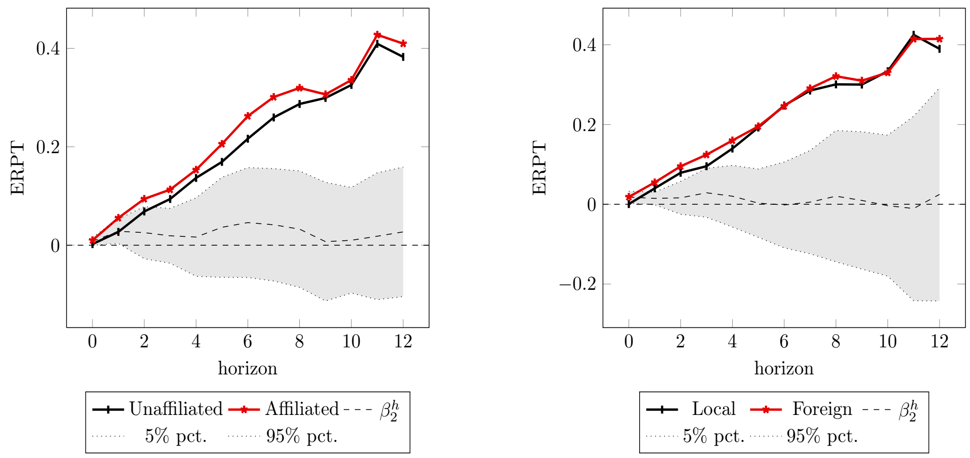
In this way, coefficient β_1 measures ERPT for the base group ($d_i^1 = 0$ and $d_i^2 = 0$), coefficients β_2 and β_3 provide inference on the difference in ERPT for observations that differ from the base group along one dimension at a time ($d_i^1 = 1$ or $d_i^2 = 1$) and β_4 indicates if ERPT differs for observations that are different from the base group along both dimensions ($d_i^1 = 1$ and $d_i^2 = 1$).[18]

Figure 8a and 8b show the results when we estimate equation 4 for local versus foreign goods and unaffiliated versus affiliated goods separately. The estimation results are presented in Table C.13 and Table C.14 respectively. From 8 it is clear that we do not find a significant difference when we only slice the data along one dimension at a time.

[18] $D_1 = 1$ when the product is part of an international brand and $d_1 = 0$ in the case of local brands. Similarly, $D_1 = 1$ in case of a foreign product and zero in case of local product.

Figure 8: Heterogeneity: International Group and Sourcing: Seperate

(a) International Group (b) Sourcing

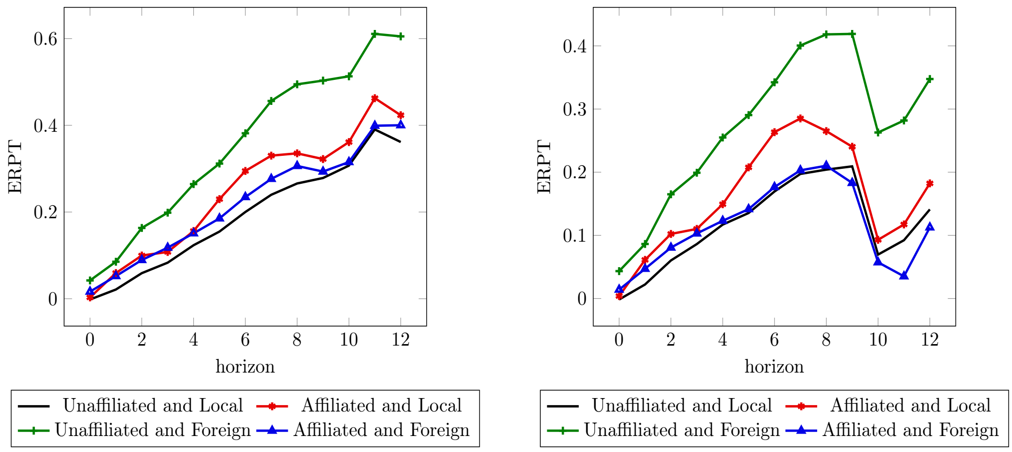


Notes: Panel (a) presents the results of equation 4 by subdividing observations on their affiliation to an international group. Panel (b) does so by subdividing goods into local and foreign goods. The variable β_2^h together with its 5% and 95% confidence intervals indicates whether the two groups exhibit a significantly different ERPT. We include 5 lags of the control variables. Confidence intervals are calculated using the Driscoll and Kraay (1998) variance estimator.

Figure 9 shows the results from estimating equation 5 without (panel (a)) and with brand fixed effects (panel (b)). In this figure the solid line indicates pass-through for local and unaffiliated products, the red line (round marker) does so for local and affiliated products, the green line (star-shaped marker) for foreign and unaffiliated products and the bl1ue line (triangular marker) for foreign and affiliated products. From Figures 9a and 9b, we see that especially the foreign products that are unaffiliated to an international group experience the largest price increase. More importantly, we observe that international groups keep the prices of their local and foreign goods close to the prices of local goods which are unaffiliated to an international group.

Figure 9: Heterogeneity: International Group and Sourcing: Joint

(a) No brand FE (b) Brand FE



Notes: We show the results from estimating equation 5 by subdividing the observations along the international group affiliation and the product origin dimensions at the same time. In each panel the solid black line indicates pass-through for local and unaffiliated products, the red line (round marker) does so for local and affilitated products, the green lin (star-shaped marker) for foreign and unaffilitated products and the blue line (triangular marker) for foreign affiliated products. Panel (a) presents the results without the inclusion of brand fixed effects and panel (b) includes brand fixed effects. In each panel we include 5 lags of control variables and estimate standard errors using the Driscoll and Kraay (1998) variance estimator.

Table 5 provides additional evidence that the foreign unaffiliated products have higher pass-through and that international brands keep their prices closer to the prices of the local and unaffiliated products. Table 5 takes the results from estimating equation 5 and performs the appropriate linear hypothesis tests to judge which of the four ERPT profiles is significantly different from one another. In each panel, we present the results for the regressions at horizon 0, 6 and 12. Panel (a) performs the estimation of equation 5 without the inclusion of brand fixed effects. Panel (b) does include brand fixed effects in the estimation in the estimation of the coefficients.

Panel (a) of Table 5 shows that after one year pass-through into consumer prices of foreign and unaffiliated goods is significantly higher than for local and unaffiliated goods. Nevertheless, this is not the case for local and foreign products that are affiliated to an international brand. This result explains why we did not find a significant difference between local and foreign products when we did not discriminate between unaffiliated and affiliated products at the same time (see Figure 8). We speculate that accounting for the presence of international brand is essential to produce the result that foreign goods experience higher ERPT compared to local ones in our sample. Second, local goods that are affiliated to an international brand are characterized a 6% higher pass-through than products that are unaffiliated to an international brand. However, foreign goods that are affiliated are characterized by a 20% lower pass-through. This is further evidence that international brands keep prices of their local and foreign products close to the prices of local and unaffiliated alternatives. To provide further robustness against the omission of fixed effects in panel 5a, we re-estimate equation 5 and include brand fixed effects as well. From panel (b) of table 5, it is clear that our conclusion does not change when we include brand fixed effects and that these results are driven by within brand variation.

This result is consistent with the work of Berman et al. (2012), Chatterjee et al. (2013) and Chen and Juvenal (2016). They argue that high performance firms, either more productive firms (in the case of Berman et al. (2012) and Chatterjee et al. (2013)) or firms producing higher quality goods (in the case of Chen and Juvenal (2016)) have lower exchange rate pass-through. Berman et al. (2012) rationalize this in a heterogenous firm setting à la Melitz (2003) in which more productive firms face a lower perceived elasticity of demand due to the fact that their marginal costs represent a smaller share in the final consumer price. Consequently, if the exchange rate of the country to which it is currently exporting for instance depreciates, more productive firms can adjust their import price more for a given change in the final consumer price leading to lower ERPT into import prices. Chen and Juvenal (2016) provide a similar argument for higher quality goods that are subject to larger distribution margins when the goods is provided to final consumers. Given that we find that affiliated products are at least twice as expensive as unaffiliated products, the international dummy seems to be a good proxy for product quality.

Table 5: Heterogeneity: International group affiliation and product origin

	h = 0		*h = 6*		*h = 12*	
Panel (a) *- no brand FE*	*F-test*	*p-value*	*F-test*	*p-value*	*F-test*	*p-value*
Local and aff. vs Local and no aff.	(.740)	.396	(4.32)**	.048	(5.51)**	.031
Foreign and no aff. vs Local and no aff.	(21.6)***	.000	(6.42)**	.018	(6.14)**	.024
Foreign and aff. vs Local and no aff.	(8.62)***	.006	(.220)	.643	(.088)	.769
Foreign and no aff. vs Local and aff.	(8.23)***	.007	(4.10)*	.054	(2.90)	.106
Foreign and aff. vs Local and aff.	(2.15)	.152	(2.47)	.129	(.029)	.864
Foreign and aff. vs Foreign and no aff.	(7.69)***	.009	(21.9)***	.000	(11.7)***	.003
Panel (b) *- brand FE*	*F-test*	*p-value*	*F-test*	*p-value*	*F-test*	*p-value*
Local and aff. vs Local and no aff.	(1.11)	.300	(4.10)*	.054	(12.8)***	.002
Foreign and no aff. vs Local and no aff.	(26.7)***	0	(10.2)***	.003	(27.5)***	.000
Foreign and aff. vs Local and no aff.	(3.45)*	.073	(.092)	.763	(1.61)	.220
Foreign and no aff. vs Local and aff.	(10.3)***	.003	(7.02)**	.014	(15.7)***	.000
Foreign and aff. vs Local and aff.	(1.07)	.309	(10.0)***	.004	(14.7)***	.001
Foreign and aff. vs Foreign and no aff.	(5.26)**	.029	(15.6)***	.000	(17.6)***	.000

Notes: This table presents the outcome of the tests to check if the ERPT profile of the 4 different categories (local and unaffiliated, foreign and unaffiliated, local and affiliated and foreign and affiliated products) is significantly different from each other. Doing so, we estimate equation 5 and perform a series of linear hypothesis tests on the coefficients. Panel (a) presents the results without inclusing brand fixed effects and panel (b) presents the results when we include brand fixed effects. At horizon 0, 6 and 12, we report the F-tests, p-values and significance levels are at the * 10%, ** 5% and *** 1% level.

5.3 Currency of invoicing

The previous section states that the currency of invoicing and the size of the shock are two possible explanations why pass-through may be higher in Kazakhstan compared to evidence from the US. In this section, we elaborate on the role of the currency of invoicing. In principle, we could exploit the fact that out data covers both the smaller 2014 devaluation and the large 2015 devaluation to test if exchange rate pass-through was higher after the larger devaluation. However, Table C.4 in appendix shows that the subsample spanning the period from January 2014 until June 2015 violates the stationarity assumption completely for the time series variables and partly for the panel variables. For this reason, we are unable to test the relevance within our empirical framework.

In contrast to the shock size channel, we are able to provide evidence that cross-country differences in the currency of invoicing could be an important driver of cross-country differences in exchange rate pass-through. Doing so, we turn to a novel scanner dataset which is obtained from an internationally active retailer that is active in Kazakhstan and 24 other countries. Among the different store types considered in this paper This dataset is extensively discussed in Colicev, Hoste, and Konings (2019). Among other data, they have provided us with information on the currency of invoicing used to import grocery products from foreign suppliers between September 2014 and December 2017. Table 6 shows the distribution of the currency of invoicing across all imported goods before and after the devaluation of August 2015. The first column of Table 6 displays sales-weighted distribution, based on the market share of the goods in total sales, and the second column price a count weighted distribution, based on the number of products that use a particular currency of invoicing. Table 6 clearly illustrates that local currency pricing is extremely rare and that the import transactions executed by this retailer are characterized by producer currency pricing and vehicle currency pricing. This is in stark contrast with the evidence provided in Gopinath and Rigobon (2008) where around 90% of US import transactions are invoiced in USD or local currency. In line with Gopinath (2015), the stark differences between the currency of invoicing distribution could be one important channel that explains the relatively high and rapid exchange rate pass-through into consumer prices.

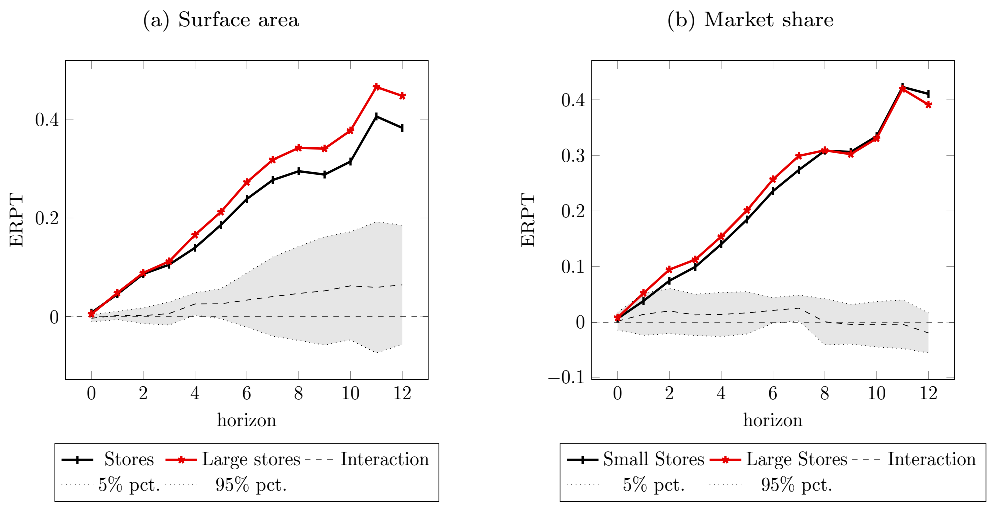
Table 6: Currency Distribution

Currency	$MKT_{Weighted}$ *(%)*	$MKT_{Unweighted}$ *(%)*
Before Depreciation		
EUR	15.26	19.68
GBP	0.00	0.02
KZT	0.01	0.03
RUB	75.71	62.86
USD	9.02	17.41
After Depreciation		
EUR	20.59	19.68
GBP	0.00	0.02
KZT	0.00	0.02
RUB	59.45	62.71
USD	19.96	17.57

Notes: This table provides the sales-weighted and unweighted distribution of the currency of invoicing before and after the depreciation of August 2015.

One obvious objection against this piece of evidence is that it is based on only a large retailer which may exhibit unrepresentative invoicing patterns compared to smaller retailers. If smaller retailers are characterized by different invoicing patterns, this would be one reason why their pass-through patterns would differ. Doing so, we estimate equation 4 this time by splitting the sample into large ($d_t = 1$) and small ($d_t = 0$) supermarkets. In this way $beta_1^h$ estimates the exchange rate pass-through for products sold in large stores and $beta_2^h$ indicates whether pass-through is different for products sold in small stores. Figure 10 shows the results from classifying the supermarket based on floor space where we adopt the standard AC Nielsen classification that a large store has a floor space above $100m^2$. Figure 10 shows the result from classifying supermarkets based on the market share of the store type. In this case, a large store type is a store type that has a market share within the top five across all store types. Both figures show that there is not a significant difference in ERPT across stores of different sizes at any horizon considered. These results are consistent across different definitions of top market share. More specifically, the results are consistent when we define a top market share as having a market share within the top three and top seven. This result is at odds with the results obtained in Antoniades and Zaniboni (2016) who find that pass-through into consumer prices is positively related to the stores market share. We consider this result as encouraging evidence that the distribution of invoice currencies for one large retailer could be representative for the greater Kazakh economy and that the currency of invoicing could play an important role in generating larger exchange rate pass-through into consumer prices.

Figure 10: Impulse response function: Store size



Notes: Here we present the results from estimaing equation 4 while subdidiving the sample into large stores. We present the coefficient estimate $\beta^h \quad \forall h = 1, \cdots, 12$ and the 95% confidence intervals which are calculated using the Driscoll and Kraay (1998) variance estimator. The left panel presents these results after subdividing the sample based on the surface area of the store. The right panel takes the store type's market share over the sample period to classify stores.

6 Conclusion

We estimate exchange rate pass-through into consumer prices in Kazakhstan in the aftermath of the depreciation of the Kazakh Tenge in August 2015. The ongoing downward pressure on global commodity prices forced the Kazakh monetary authority to abandon the fixed exchange rate policy and to introduce a floating exchange rate subsequently. We use this large depreciation to provide new micro evidence on the timing and extent of the exchange rate pass-through into consumer prices. To do so, we collect monthly scanner data of 4,863 different fast-moving consumer goods observed throughout the country in different stores obtained from AC Nielsen Kazakhstan.

We use Local Projections which is ideally suited for instances when the depreciation is large and persistent. First, through simulations we show that Local Projections is robust to the presence of serial correlation in the exogenous shock which is typically present in large devaluation episode because of staggered adjustment over time or by over-shooting. Second, compared to the empirical methods which are currently used to estimate ERPT, Local Projections is able to more flexibly control for past economic information.

Our study has the following implications. First, while previous studies have focused on cross-sectional heterogeneity in EPRT, we investigate the dynamic effects of a large and unexpected currency shock on consumer prices. We find that, consistent with a recent strand in the literature that incorporates the dominance of the US dollar in the determination of international prices, the exchange rate pass-through happens instantaneously. Thus, we contribute to the growing literature on the timing of ERPT and on the causal effect of exchange rates on consumer prices (Nakamura and Zerom (2010), Goldberg and Hellerstein (2013) and Bonadio et al. (2018)).

Second, our study complements the previous research that investigates the ERPT into consumer prices into the US, by studying the ERPT into consumer prices in a small emerging economy. It has been established that the strength of the US Dollar in international trade and international financial transactions induces significant asymmetries in the propagation of shocks across countries. For this reason, obtaining evidence on exchange rate pass-through into consumer prices of a small open economy provides new micro-foundations for new open macroeconomic models to predict the effect of currency fluctuations on domestic prices. We find that the long run level (ERPT after 12 months) already materialized after six to nine months which contrasts with slow price adjustment in the USD. Also, our estimates demonstrate that pass-through into consumer prices is between 25% and 34% after 12 months. Consistent with the seminal work by Burstein et al. (2005), ERPT into consumer prices was considerably larger compared to evidence from the US. In addition, we show, using data from a large international retailer, that imports concerning grocery products into Kazakhstan are not invoiced in local currency. This fact is consistent with the literature (e.g. Gopinath (2015)) that explains cross-country differences in pass-through by cross-country differences in the distribution of the currency of invoicing.

Third, we document the presence of considerable cross-sectional heterogeneity. We investigate the results by whether the goods are foreign (local) and (un) affiliated to an international group. We find that foreign (local) unaffiliated goods experience the largest (smallest) price increase after the exchange rate shock. In contrast, the foreign and local affiliated goods experience a similar EPRT into consumer prices. For example, local goods that are affiliated to an international brand are characterized a 6% higher pass-through than products that are unaffiliated to an international brand. This result echoes the work of Berman et al. (2012), Chatterjee et al. (2013) and Chen and Juvenal (2016) who show that more productive firms and higher quality firms have lower exchange rate pass-through.

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A Simulations

This section explains the setup and the results of the simulations that show that estimating exchange rate pass-through in the presence of structure or persistency in the exchange rate requires the use of Local Projections instead of earlier proposed Distributed Lag models. We show that this under various types of structure or persistency in the exchange rate and we show that this is true independent of the presence of dynamics in the dependent variable conditional on the explanatory variables, in this case product-specific prices. First, we describe the setup and the data generating processes in a general way. Next, we explain the simulation method when we assume that the independent variable is conditional on the explanatory variables serially uncorrelated and we discuss the results of these simulations. Finally, we allow for richer dynamics in the dependent variable and show that the results remain unchanged.

A.1 No conditional correlation

The central question is to know the dynamic effect of a well-identified shock to the independent variable, x, on the dependent variable, y. Since we are interested in the dynamic effect of x on y, we assume that the effect of x on y will not be strictly contemporaneous but that this effect may last for a couple of periods. The exchange pass-through literature has proposed the use of Distributed Lags models to estimate the dynamic effects of the exchange rate, in this case the independent variable x, on some price variable, in this case the dependent variable y. Such a distributed lag model is in its simplest form given by:

$$y_t = \alpha + \sum_{l=1}^{L} \beta_l x_{t-l} + \varepsilon_t \tag{A.1}$$

When the dependent variable is not a function of its own lagged values, the sum of the coefficients

$beta_l$ is then considered to be dynamic multiplier at horizon H. However, a crucial, but often implicit, assumption is that the independent variable itself may not be a function of its own lagged values or have a dynamic structure itself. This because when estimating the effect of the independent variable at time $t-l$ on the dependent variable at time t, the value of the independent variable in the next period is kept fixed. However, if the independent variable is characterized by persistence, one cannot capture the dynamic behaviour of the complete system as the sole estimation of the distributed lag model does not provide information on the dynamic behaviour of the independent variable.

One possible solution to this problem is the joint estimation of the distributed lag model and a specifcation that models the structure in the independent variable, which would result in a VAR estimation. Another related solution is to allow for these dynamics in the independent variable without having to model them explicitly. For this reason, we propose Local Projections to tackle this question. Local Projections were proposed by Jordà (2005) and are a less-efficient, but more robust alternative to VARs and thus allow for these rich dynamics in the independent variable. Again, Local Projections in its simplest form and that y is not a function of of its own lagged values and is serially uncorrelated conditional on the explanatoty variables:

$$y_t^h = \alpha + \beta^h x_t + \sum_{l=1}^{L} \gamma_l^h x_{t-l} + \varepsilon_t \tag{A.2}$$

For the simulations, we consider three different data generating processes of the independent variable. First, we assume that the independent variable is White Noise and is not characterized by serial correlation. Second, we assume that there is a small degree of serial correlation in the independent variable by assuming its data generating process is AR(1) with $\rho = 0.2$. Third, we model the data generating process of the independent variable as an AR(2) with $\rho_1 = 0.4$ and $\rho_2 = 0.3$ to allow for richer dynamics and more persistency. Given that $\rho_1 + \rho_2 < 1$ we make sure that the independent variable remains stationary.[19]

From table A.1 we see that in the case of a White Noise process for the independent variable that both the Distributed Lag model and Local Projections recover the true dynamic multiplier which denoted in the column $\frac{\partial y^h}{\partial x}$. When there are no dynamics in the independent variable and the dependent variable is not a function of its own lags, an impulse to the independent variable will die out after two periods. When we switch our attention to columns that provide the results for the case of an AR(1) process, we see that the Distributed Lag model no longer recovers the true dynamic multiplier. This is because estimating the Distributed Lag model does not provide us with information on the dynamics associated with the independent variable. Note that in the case of Local Projections we do not explicitly estimate the relation between the independent variable and its lagged values, but we still allow for this relation. If the independent variable is characterized by even more persistency, the AR(2)-case, the deviation of the distributed lag model from the true dynamic multiplier becomes even worse.

[19]The Monte-Carlo simulations are implemented in the following way. First, we generate two samples of 100,000 white noise error terms, one for the independent and one for the dependent variable. Next, we sample 10,000 observations and construct the independent variable according to one of the three cases and construct the dependent variable according in the following way:

$$y_t = 0.4x_{t-1} + 0.3x_{t-2} + e_t$$

. Given data on both x and y, we compute the dynamic multipliers either with a DL(2) and with Local Projections.

Table A.1: Simulations: No conditional serial correlation

	White noise			*AR(1)*			*AR(2)*		
Horizon	$\frac{\partial y^h}{\partial x}$	$\hat{\beta}^h_{DL}$	$\hat{\beta}^h_{LP}$	$\frac{\partial y^h}{\partial x}$	$\hat{\beta}^h_{DL}$	$\hat{\beta}^h_{LP}$	$\frac{\partial y^h}{\partial x}$	$\hat{\beta}^h_{DL}$	$\hat{\beta}^h_{LP}$
h = 1	.4	(.399)	(.400)	.4	(.399)	(.400)	.4	(.399)	(.400)
	.4	(.010)	(.009)	.4	(.010)	(.009)	.4	(.010)	(.009)
h = 2	.3	(.299)	(.300)	.38	(.299)***	(.380)	.46	(.300)***	(.460)
	.3	(.011)	(.011)	.38	(.011)	(.011)	.46	(.011)	(.011)
h = 3	0	(.000)	(-.00)	.076	(.000)***	(.075)	.304	(.000)***	(.303)
	0	(.010)	(.011)	.076	(.010)	(.011)	.304	(.011)	(.011)
h = 4	0	(-.00)	(-.00)	.0152	(-.00)	(.015)	.2596	(-.00)***	(.259)
	0	(.010)	(.010)	.0152	(.011)	(.011)	.2596	(.010)	(.011)

Notes: This table presents the results of the simulations when the data generating process of the dependent variable does not contain dynamics. We report the results for three different data-generating processes for the indenpendent variable. First, we assume that it is a white noise. Second, we assume a small level of serial correlation by assuming AR(1). Third, we allow for richer dynamics and more persistency by assuming AR(2). Each of these cases reports the true dynamic multiplier and the estimated multiplier using a DL-model and when using a LP-model. The significance level associated with the coefficient refers to a t-test to test whether the dynamic multiplier is significantly different from the true dynamic multiplier. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

A.2 Conditional serial correlation

The previous section did not allow for the dependent variable to be serially correlated conditional on the explanatory variables. For instance, we did not allow for dependent variable to be function of its own lagged values or to exhibit serial correlation conditional on the explanatory variables. This section allows for such dependencies and we adjust equations A.1 and A.2 to control for these dependencies. For the Distributed Lag model we estimate:

$$y_t = \alpha + \sum_{l=1}^{L} \beta_l x_{t-l} + \sum_{i=1}^{I} \theta_l y_{t-i} + \varepsilon_t. \tag{A.3}$$

For Local Projections we estimate:

$$y_t^h = \alpha + \beta^h x_t + \sum_{l=1}^{L} \gamma_l^h x_{t-l} + \sum_{i=1}^{I} \theta_l y_{t-i} + \varepsilon_t \tag{A.4}$$

Looking at table A.2 we see very similar results as the ones expressed in table A.1.[20] In

[20]The implementation of the Monte-Carlo simulations is almost identical to the ones where we do not allow for conditional serial correlation in the dependent variable. The only difference is in the data generating process of the dependent variable where we allow that the dependent variable is determined by its lagged values as well. As a result, we generate the dependent variable using the following specification:

$$y_t = 0.4x_{t-1} + 0.3x_{t-2} + 0.4y_{t-1} + 0.3y_{t-2} + e_t$$

the case when the independent variable does not have any structure itself, both the Distributed Lag model as the local projections are able to recover the true dynamic multipliers. We need to note that the dynamic multipliers implied by estimating the Distributed Lag model are no longer equal to β_l because of the dependence of the dependent variable on its own lagged values. In this way, the effect of a one unit impluse in the independent variable will not work through its next values, but also through the next values of the dependent variable. We turn to the cases when there is serial correlation in the indepedent variable we see that the distributed lag model underestimates the dynamic multipliers again because it does not account for this positive structure in the independent variable. Similar to the results in table A.1, Local Projections does recover the true dynamic multipliers in the case of conditional serial correlation in the dependent variable.

Table A.2: Simulations: Dynamics in the dependent variable

	White noise			*AR(1)*			*AR(2)*		
Horizon	$\frac{\partial y^h}{\partial x}$	$\hat{\beta}^h_{DL}$	$\hat{\beta}^h_{LP}$	$\frac{\partial y^h}{\partial x}$	$\hat{\beta}^h_{DL}$	$\hat{\beta}^h_{LP}$	$\frac{\partial y^h}{\partial x}$	$\hat{\beta}^h_{DL}$	$\hat{\beta}^h_{LP}$
h = 1	.4	(.399)	(.398)	.4	(.399)	(.398)	.4	(.399)	(.398)
	.4	(.010)	(.010)	.4	(.010)	(.010)	.4	(.010)	(.010)
h = 2	.46	(.459)	(.458)	.54	(.459)***	(.538)	.62	(.460)***	(.618)
	.46	(.012)	(.013)	.54	(.011)	(.013)	.62	(.010)	(.013)
h = 3	.304	(.304)	(.301)	.412	(.304)***	(.409)	.672	(.304)***	(.669)
	.304	(.011)	(.013)	.412	(.010)	(.013)	.672	(.009)	(.014)
h = 4	.2596	(.259)	(.258)	.342	(.259)***	(.340)	.7144	(.259)***	(.712)
	.2596	(.012)	(.012)	.342	(.011)	(.013)	.7144	(.008)	(.014)

Notes: This table presents the results of the simulations when the data generating process of the dependent variable does contain dynamics. We report the results for three different data-generating processes for the indenpendent variable. First, we assume that it is a white noise. Second, we assume a small level of serial correlation by assuming AR(1). Third, we allow for richer dynamics and more persistency by assuming AR(2). Each of these cases reports the true dynamic multiplier and the estimated multiplier using a DL-model and when using a LP-model. The significance level associated with the coefficient refers to a t-test to test whether the dynamic multiplier is significantly different from the true dynamic multiplier. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

B Figures

C Tables

Table C.1: Exported commodities in 2015

Nr.	*Commodity*	*SITC (3-Digit)*	*Share (%)*	*Cumm. Share (%)*
1	Crude and Bituminous Oil	333	58.26	58.26
2	Gas, natural and manufactured	341	5.19	63.45
3	Radioactive Material	524	5.12	68.57
4	Copper	682	4.27	72.84
5	Refined Petroleum Products	334	3.01	75.85
6	Iron and Ferro-Alloys	671	2.96	78.8
7	Ores and concentrates of base metals, nes	287	2.14	80.95
8	Iron and Steel plates/sheets	674	1.66	82.61
9	Wheat and meslin, unmilled	41	1.5	84.1
10	Zinc	686	1.25	85.36
11	Meal/Flour of wheat/meslin	46	1.08	86.43
12	Silver and Platinum metals	681	1.06	87.49
13	Coal, lignite and peat	322	1.06	88.55
14	Iron ore and concentrates	281	.88	89.43
15	Aluminium	684	.87	90.3
16	Oxides and Halogen Salts	522	.77	91.07
17	Sulphur and unroasted iron pyrites	274	.71	91.78
18	Iron and Steel (primary forms)	672	.61	92.4
19	Gold (not ores or concentrates)	971	.46	92.86
20	Lead	685	.41	93.27

Notes: The data is taken from UN Comtrade. The table presents the top 20 of most exported commodities by Kazakh companies in 2015. The share and cummulative share are calculated with respect to the total export of Kazakhstan in 2015 as reported by UN Comtrade.

Table C.2: Import Partners in 2015

Nr.	*Partner*	*Share (%)*	*Cumm. Share(%)*
1	Russian Federation	34.45	34.45
2	China	16.64	51.09
3	Germany	6.5	57.59
4	USA	4.86	62.44
5	Italy	3.84	66.29
6	Ukraine	2.71	68.99
7	Turkey	2.43	71.42
8	Uzbekistan	2.37	73.8
9	France	2.19	75.99
10	Rep. of Korea	1.99	77.98
11	Japan	1.91	79.89
12	Belarus	1.6	81.49
13	United Kingdom	1.32	82.8
14	Poland	1.11	83.92
15	Netherlands	1.02	84.94
16	Canada	.83	85.77
17	India	.79	86.56
18	Lithuania	.72	87.28
19	Spain	.72	88
20	Viet Nam	.64	88.64

Notes: The data is taken from UN Comtrade. The table provides the top 20 countries from which Kazakhstan imports. The share and cummulative share are calculated based upon total imports in 2015 as reported by UN Comtrade.

Table C.3: Univariate unit root Test: Time series variables

Variable	*No trend*			*Trend*		
	1 lag	*2 lags*	*3 lags*	*1 lag*	*2 lags*	*3 lags*
Levels						
Oil Price	-1.19	-1.20	-.95	-1.42	-1.75	-1.57
	(0.67)	(0.66)	(0.76)	(0.85)	(0.72)	(0.80)
CPI	.22	.52	.25	-2.11	-1.75	-1.98
	(0.97)	(0.98)	(0.97)	(0.53)	(0.72)	(0.60)
Log differences						
Oil Price	-3.77	-3.74	-2.91			
	(0.00)***	(0.00)***	(0.04)**			
CPI	-3.67	-2.79	-3.02			
	(0.00)***	(0.05)*	(0.03)**			

Notes: This table presents the univariate unit root tests for the Oil price and domestic inflation variables. We use an Augmented Dickey-Fuller test (ADF) where we allow for different forms of autocorrelation in the residuals. The maximal number of lags is chosen in accordance to Newey and West (1987) rule of thumb which implies $\text{Lag}_{max} = \sqrt[4]{T}$. For the variables in levels we ran a test with a constant and no trend and a test with both a constant and a trend, for the log differences we only included a constant. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

Table C.4: Univariate unit root Test: Time series variables - Pre August 2015

Variable	*No trend*			*Trend*		
	1 lag	*2 lags*	*3 lags*	*1 lag*	*2 lags*	*3 lags*
Levels						
Oil Price	-.65	-.87	-.83	-1.80	-3.05	-3.04
	(0.85)	(0.79)	(0.80)	(0.70)	(0.11)	(0.12)
CPI	-1.35	-1.37	-.33	-2.57	-2.39	-2.06
	(0.60)	(0.59)	(0.91)	(0.29)	(0.38)	(0.56)
Log differences						
Oil Price	-2.03	-1.99	-1.97			
	(0.27)	(0.28)	(0.29)			
CPI	-2.76	-2.10	-1.98			
	(0.06)*	(0.24)	(0.29)			

Notes: This table presents the univariate unit root tests for the Oil price and domestic inflation variables in the sample period before August 2015. We use an Augmented Dickey-Fuller test (ADF) where we allow for different forms of autocorrelation in the residuals. The maximal number of lags is chosen in accordance to Newey and West (1987) rule of thumb which implies $\text{Lag}_{max} = \sqrt[4]{T}$. For the variables in levels we ran a test with a constant and no trend and a test with both a constant and a trend, for the log differences we only included a constant. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

Table C.5: Panel unit root Tests - Pre August 2015

Variable	*No trend*			*Trend*		
	1 lag	*2 lags*	*3 lags*	*1 lag*	*2 lags*	*3 lags*
Levels						
Exchange rate	(-3.17)*	(-2.16)	(-1.79)	(-4.04)**	(-2.79)	(-2.36)
Labour cost	(-1.92)	(-1.89)	(-1.28)	(-2.03)	(-1.87)	(-1.42)
Product price	(-1.85)	(-1.48)	(-1.37)	(-2.46)	(-2.10)	(-1.90)
Log differences						
Exchange rate	(-4.18)***	(-3.14)*	(-2.05)			
Labour cost	(-2.73)	(-2.05)	(-1.62)			
Product price	(-3.13)*	(-2.12)	(-1.80)			

Notes: This table presents the panel unit root tests for the trade-weighted exchange rate, the trade-weighted labour unit cost index and the product prices. We use the panel unit root test proposed by Pesaran (2007) which is robust to cross-sectional dependence and where we allow for different forms of autocorrelation in the residuals. The maximal number of lags is chosen in accordance to Newey and West (1987) rule of thumb which implies $\text{Lag}_{max} = \sqrt[4]{T}$. For the variables in levels we ran a test with a constant and no trend and a test with both a constant and a trend, for the log differences we only included a constant. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

Table C.6: Baseline Results: 4 lags

Horizon	$\hat{\beta}^h$	*p-value*	$5\% - CI$	$95\% - CI$	N	R^2
h = 0	0.008***	0.0041	0.00290	0.01397	122,822	0.057
h = 1	0.046***	0.0035	0.01631	0.07510	117,561	0.123
h = 2	0.086***	0.0023	0.03353	0.13852	112,750	0.192
h = 3	0.106***	0.0027	0.04003	0.17145	108,074	0.245
h = 4	0.140***	0.0052	0.04585	0.23508	103,465	0.280
h = 5	0.183***	0.0039	0.06440	0.30076	98,852	0.306
h = 6	0.221***	0.0016	0.09320	0.34949	94,307	0.319
h = 7	0.254***	0.0006	0.12215	0.38684	89,933	0.326
h = 8	0.267***	0.0007	0.12672	0.40656	85,614	0.334
h = 9	0.253***	0.0003	0.13139	0.37471	81,330	0.345
h = 10	0.262***	0.0004	0.13486	0.38954	77,085	0.363
h = 11	0.257***	0.0004	0.13139	0.38175	72,900	0.377
h = 12	0.254***	0.0004	0.13185	0.37707	68,741	0.400

Notes: This table presents the results at all horizons after estimating equation 1 using the monthly sample and while including 4 lags of control variables. We calculate standard erros based on the Driscoll and Kraay (1998) variance estimator. In this way we correct the standard errors for the presence conditional heteroskedasticity, aribtrary spatial correlation and autocorrelation. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

Table C.7: Baseline Results: 5 lags

Horizon	$\hat{\beta}^h$	*p-value*	$5\% - CI$	$95\% - CI$	N	R^2
h = 0	0.008***	0.0007	0.00374	0.01245	119,623	0.058
h = 1	0.043***	0.0003	0.02154	0.06453	114,390	0.127
h = 2	0.079***	0.0010	0.03521	0.12256	109,596	0.198
h = 3	0.096***	0.0010	0.04307	0.14939	104,908	0.251
h = 4	0.129***	0.0008	0.05936	0.19772	100,301	0.290
h = 5	0.174***	0.0002	0.09407	0.25485	95,696	0.320
h = 6	0.223***	0.0000	0.13547	0.31025	91,151	0.335
h = 7	0.260***	0.0000	0.16576	0.35465	86,779	0.342
h = 8	0.283***	0.0000	0.18235	0.38398	82,458	0.353
h = 9	0.286***	0.0000	0.18804	0.38375	78,176	0.370
h = 10	0.308***	0.0000	0.19739	0.41771	73,937	0.392
h = 11	0.306***	0.0000	0.19019	0.42130	69,757	0.409
h = 12	0.340***	0.0000	0.21811	0.46120	65,594	0.440

Notes: This table presents the results at all horizons after estimating equation 1 using the monthly sample and while including 5 lags of control variables. We calculate standard erros based on the Driscoll and Kraay (1998) variance estimator. In this way we correct the standard errors for the presence conditional heteroskedasticity, aribtrary spatial correlation and autocorrelation with a lag length up to 13. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

Table C.8: Baseline Results: 6 lags

Horizon	$\hat{\beta}^h$	*p-value*	$5\% - CI$	$95\% - CI$	N	R^2
h = 0	0.009***	0.0001	0.00483	0.01332	116,368	0.060
h = 1	0.043***	0.0011	0.01906	0.06771	111,165	0.131
h = 2	0.080***	0.0028	0.03043	0.13030	106,362	0.202
h = 3	0.105***	0.0021	0.04188	0.16735	101,677	0.256
h = 4	0.140***	0.0010	0.06249	0.21673	97,077	0.296
h = 5	0.194***	0.0001	0.11017	0.27731	92,477	0.330
h = 6	0.244***	0.0000	0.15079	0.33736	87,934	0.347
h = 7	0.285***	0.0000	0.17528	0.39567	83,565	0.357
h = 8	0.302***	0.0001	0.17895	0.42480	79,245	0.378
h = 9	0.325***	0.0002	0.18006	0.47061	74,967	0.404
h = 10	0.362***	0.0001	0.21358	0.51032	70,732	0.434
h = 11	0.373***	0.0004	0.19435	0.55127	66,547	0.456
h = 12	0.282***	0.0000	0.17988	0.38372	62,382	0.504

Notes: This table presents the results at all horizons after estimating equation 1 using the monthly sample and while including 6 lags of control variables. We calculate standard erros based on the Driscoll and Kraay (1998) variance estimator. In this way we correct the standard errors for the presence conditional heteroskedasticity, aribtrary spatial correlation and autocorrelation with a lag length up to 13. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

Table C.9: Baseline results - Dynamic: 4 lags

Horizon	*Coef.*	$\hat{\beta}_i^h$	*p-value*	*N*	R^2		
h = 0	i = i	0.005	0.2185	-0.00283	0.01189	120,675	0.077
h = 0	i = 2	-0.138***	0.0000	-0.16739	-0.10786		
h = 1	i = i	0.040**	0.0122	0.00932	0.07015	115,562	0.153
h = 1	i = 2	-0.216***	0.0000	-0.24043	-0.19224		
h = 2	i = i	0.080***	0.0046	0.02675	0.13298	110,824	0.217
h = 2	i = 2	-0.229***	0.0000	-0.24378	-0.21479		
h = 3	i = i	0.100***	0.0050	0.03291	0.16690	106,212	0.266
h = 3	i = 2	-0.234***	0.0000	-0.25490	-0.21267		
h = 4	i = i	0.135***	0.0080	0.03832	0.23071	101,620	0.297
h = 4	i = 2	-0.232***	0.0000	-0.25731	-0.20649		
h = 5	i = i	0.176***	0.0058	0.05594	0.29663	97,066	0.322
h = 5	i = 2	-0.241***	0.0000	-0.26678	-0.21606		
h = 6	i = i	0.213***	0.0025	0.08300	0.34321	92,701	0.335
h = 6	i = 2	-0.271***	0.0000	-0.30740	-0.23505		
h = 7	i = i	0.246***	0.0009	0.11230	0.37990	88,386	0.343
h = 7	i = 2	-0.300***	0.0000	-0.33655	-0.26288		
h = 8	i = i	0.258***	0.0011	0.11568	0.39959	84,113	0.351
h = 8	i = 2	-0.320***	0.0000	-0.37186	-0.26813		
h = 9	i = i	0.242***	0.0005	0.11951	0.36450	79,866	0.360
h = 9	i = 2	-0.342***	0.0000	-0.39722	-0.28669		
h = 10	i = i	0.249***	0.0006	0.12062	0.37694	75,679	0.377
h = 10	i = 2	-0.360***	0.0000	-0.42921	-0.29038		
h = 11	i = i	0.244***	0.0007	0.11801	0.37005	71,531	0.389
h = 11	i = 2	-0.349***	0.0000	-0.42324	-0.27529		
h = 12	i = i	0.241***	0.0007	0.11725	0.36488	67,434	0.411
h = 12	i = 2	-0.362***	0.0000	-0.43298	-0.29135		

Notes: This table presents the results after estimating equation 3 using 4 lags of control variables. We calculate standard erros based on the Driscoll and Kraay (1998) variance estimator. In this way we correct the standard errors for the presence conditional heteroskedasticity, aribtrary spatial correlation and autocorrelation with a lag length up to 13. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

Table C.10: Baseline results - Dynamic: 5 lags

Horizon	*Coef.*	$\hat{\beta}_i^h$	*p-value*	*N*	R^2		
h = 0	i = 1	0.004*	0.0999	-0.00083	0.00904	117,561	0.080
h = 0	i = 2	-0.139***	0.0000	-0.16752	-0.11041		
h = 1	i = 1	0.037***	0.0015	0.01530	0.05824	112,464	0.158
h = 1	i = 2	-0.220***	0.0000	-0.24223	-0.19692		
h = 2	i = 1	0.072***	0.0019	0.02910	0.11563	107,740	0.223
h = 2	i = 2	-0.233***	0.0000	-0.24760	-0.21789		
h = 3	i = 1	0.090***	0.0019	0.03658	0.14373	103,121	0.273
h = 3	i = 2	-0.239***	0.0000	-0.25981	-0.21830		
h = 4	i = 1	0.122***	0.0013	0.05253	0.19220	98,534	0.309
h = 4	i = 2	-0.237***	0.0000	-0.26202	-0.21211		
h = 5	i = 1	0.168***	0.0003	0.08666	0.24916	93,987	0.336
h = 5	i = 2	-0.246***	0.0000	-0.26803	-0.22389		
h = 6	i = 1	0.214***	0.0000	0.12572	0.30249	89,618	0.351
h = 6	i = 2	-0.275***	0.0000	-0.30903	-0.24149		
h = 7	i = 1	0.251***	0.0000	0.15582	0.34657	85,305	0.359
h = 7	i = 2	-0.301***	0.0000	-0.33547	-0.26700		
h = 8	i = 1	0.274***	0.0000	0.17180	0.37565	81,030	0.370
h = 8	i = 2	-0.319***	0.0000	-0.36323	-0.27551		
h = 9	i = 1	0.275***	0.0000	0.17647	0.37312	76,787	0.385
h = 9	i = 2	-0.333***	0.0000	-0.37938	-0.28601		
h = 10	i = 1	0.295***	0.0000	0.18163	0.40750	72,603	0.405
h = 10	i = 2	-0.345***	0.0000	-0.40245	-0.28812		
h = 11	i = 1	0.295***	0.0001	0.17553	0.41347	68,458	0.420
h = 11	i = 2	-0.328***	0.0000	-0.39384	-0.26269		
h = 12	i = 1	0.328***	0.0000	0.20244	0.45329	64,360	0.450
h = 12	i = 2	-0.336***	0.0000	-0.39515	-0.27663		

Notes: This table presents the results after estimating equation 3 using 5 lags of control variables. We calculate standard erros based on the Driscoll and Kraay (1998) variance estimator. In this way we correct the standard errors for the presence conditional heteroskedasticity, aribtrary spatial correlation and autocorrelation with a lag length up to 13. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

Table C.11: Baseline results - Dynamic: 6 lags

Horizon	*Coef.*	$\hat{\beta}_i^h$	*p-value*	*N*	R^2		
h = 0	i = 1	0.005**	0.0473	0.00007	0.01021	114,390	0.081
h = 0	i = 2	-0.139***	0.0000	-0.16793	-0.11039		
h = 1	i = 1	0.038***	0.0037	0.01336	0.06188	109,318	0.161
h = 1	i = 2	-0.221***	0.0000	-0.24371	-0.19786		
h = 2	i = 1	0.074***	0.0047	0.02495	0.12349	104,588	0.227
h = 2	i = 2	-0.234***	0.0000	-0.24931	-0.21928		
h = 3	i = 1	0.099***	0.0034	0.03595	0.16169	99,971	0.278
h = 3	i = 2	-0.241***	0.0000	-0.26169	-0.21978		
h = 4	i = 1	0.134***	0.0016	0.05609	0.21120	95,392	0.314
h = 4	i = 2	-0.238***	0.0000	-0.26278	-0.21304		
h = 5	i = 1	0.187***	0.0001	0.10286	0.27154	90,848	0.346
h = 5	i = 2	-0.245***	0.0000	-0.26840	-0.22244		
h = 6	i = 1	0.236***	0.0000	0.14145	0.32967	86,481	0.363
h = 6	i = 2	-0.277***	0.0000	-0.31204	-0.24247		
h = 7	i = 1	0.277***	0.0000	0.16626	0.38823	82,168	0.374
h = 7	i = 2	-0.303***	0.0000	-0.34006	-0.26544		
h = 8	i = 1	0.293***	0.0001	0.16859	0.41765	77,895	0.396
h = 8	i = 2	-0.321***	0.0000	-0.36272	-0.27846		
h = 9	i = 1	0.313***	0.0003	0.16453	0.46236	73,656	0.419
h = 9	i = 2	-0.328***	0.0000	-0.37164	-0.28394		
h = 10	i = 1	0.348***	0.0001	0.19514	0.50076	69,478	0.447
h = 10	i = 2	-0.343***	0.0000	-0.39108	-0.29580		
h = 11	i = 1	0.361***	0.0007	0.17796	0.54400	65,328	0.467
h = 11	i = 2	-0.322***	0.0000	-0.38248	-0.26233		
h = 12	i = 1	0.270***	0.0000	0.16643	0.37267	61,229	0.514
h = 12	i = 2	-0.322***	0.0000	-0.37031	-0.27375		

Notes: This table presents the results after estimating equation 3 using 6 lags of control variables. We calculate standard erros based on the Driscoll and Kraay (1998) variance estimator. In this way we correct the standard errors for the presence conditional heteroskedasticity, aribtrary spatial correlation and autocorrelation with a lag length up to 13. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

Table C.12: Heterogeneity: Observations per subsample

Dummy	$d_i = 0$	$d_i = 1$	*Total*
Non-Food vs Food Products	31,680	146,880	178,560
Small vs Large Stores (m^2)	115,200	59,040	174,240
Small vs Large Stores (sales)	129,800	48,760	178,560
Small vs Large Products	162,019	16,541	178,560
Small vs Large Brands	97,300	81,260	178,560
International group: No vs Yes	61,992	116,568	178,560
Foreign Sourcing: No vs Yes	116,424	62,136	178,560
Group and Sourcing:			
Stand-alone and Local:	122,724	55,836	178,560
Int. Group and Local:	117,972	60,588	178,560
Stand-alone and Foreign:	172,404	6,156	178,560
Int. Group and Foreign:	122,580	55,980	178,560

Notes: We provide the number of observations in each subsample analysis executed in part 5.2.2.

Table C.13: Heterogeneity: International Group

Horizon	*Coef.*	$\hat{\beta}_i^h$	*p-value*	*N*	R^2
h = 0	i = 1	0.002	0.4616	119,623	0.058
	i = 2	0.008*	0.0561		
h = 1	i = 1	0.027***	0.0000	114,390	0.127
	i = 2	0.028**	0.0275		
h = 2	i = 1	0.069***	0.0000	109,596	0.199
	i = 2	0.026	0.3304		
h = 3	i = 1	0.094***	0.0000	104,908	0.255
	i = 2	0.019	0.4875		
h = 4	i = 1	0.137***	0.0000	100,301	0.295
	i = 2	0.017	0.6730		
h = 5	i = 1	0.169***	0.0000	95,696	0.322
	i = 2	0.036	0.4674		
h = 6	i = 1	0.216***	0.0000	91,151	0.339
	i = 2	0.046	0.4029		
h = 7	i = 1	0.260***	0.0000	86,779	0.346
	i = 2	0.041	0.4595		
h = 8	i = 1	0.287***	0.0000	82,458	0.356
	i = 2	0.033	0.5723		
h = 9	i = 1	0.299***	0.0000	78,176	0.372
	i = 2	0.007	0.9020		
h = 10	i = 1	0.326***	0.0000	73,937	0.395
	i = 2	0.010	0.8471		
h = 11	i = 1	0.409***	0.0000	69,757	0.418
	i = 2	0.018	0.7693		
h = 12	i = 1	0.383***	0.0000	65,594	0.442
	i = 2	0.027	0.6698		

Notes: This table presents the results after estimating equation 4 by seperating the monthly sample into two groups. We calculate standard erros based on the Driscoll and Kraay (1998) variance estimator. In this way we correct the standard errors for the presence conditional heteroskedasticity, aribtrary spatial correlation and autocorrelation with a lag length up to 13. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

Table C.14: Heterogeneity: International sourcing

Horizon	*Coef.*	$\hat{\beta}_i^h$	*p-value*	*N*	R^2
h = 0	i = 1	0.001	0.8318	119,623	0.059
	i = 2	0.018**	0.0191		
h = 1	i = 1	0.040***	0.0002	114,390	0.127
	i = 2	0.015*	0.0661		
h = 2	i = 1	0.079***	0.0000	109,596	0.199
	i = 2	0.016	0.4277		
h = 3	i = 1	0.095***	0.0001	104,908	0.255
	i = 2	0.029	0.3421		
h = 4	i = 1	0.140***	0.0000	100,301	0.295
	i = 2	0.020	0.5934		
h = 5	i = 1	0.192***	0.0000	95,696	0.322
	i = 2	0.003	0.9449		
h = 6	i = 1	0.248***	0.0000	91,151	0.339
	i = 2	-0.002	0.9750		
h = 7	i = 1	0.285***	0.0000	86,779	0.346
	i = 2	0.005	0.9316		
h = 8	i = 1	0.301***	0.0000	82,458	0.356
	i = 2	0.020	0.7996		
h = 9	i = 1	0.300***	0.0000	78,176	0.372
	i = 2	0.010	0.9078		
h = 10	i = 1	0.334***	0.0000	73,937	0.395
	i = 2	-0.003	0.9677		
h = 11	i = 1	0.425***	0.0000	69,757	0.418
	i = 2	-0.011	0.9244		
h = 12	i = 1	0.390***	0.0000	65,594	0.442
	i = 2	0.025	0.8467		

Notes: This table presents the results after estimating equation 4 by seperating the monthly sample into two groups. We calculate standard erros based on the Driscoll and Kraay (1998) variance estimator. In this way we correct the standard errors for the presence conditional heteroskedasticity, aribtrary spatial correlation and autocorrelation with a lag length up to 13. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

Table C.15: Heterogeneity: International sourcing

Horizon	*Coef.*	$\hat{\beta}_i^h$	*p-value*	*N*	R^2
h = 0	i = 1	-0.002	0.5375	119,623	0.059
	i = 2	0.005	0.3965		
	i = 3	0.044***	0.0001		
	i = 4	-0.031***	0.0007		
h = 6	i = 1	0.200***	0.0000	91,151	0.340
	i = 2	0.095**	0.0488		
	i = 3	0.182**	0.0185		
	i = 4	-0.242***	0.0001		
h = 12	i = 1	0.361***	0.0000	65,594	0.442
	i = 2	0.062**	0.0312		
	i = 3	0.244**	0.0240		
	i = 4	-0.267***	0.0003		

Notes: This table presents the results after estimating equation 5 by seperating the monthly sample based on affiliation to an international group and based on whether the product is sourced domestically or from abroad. The coefficient β_1^h indicates pass-through for domestic goods without an international group affiliation, $\beta_1^h + \beta_2^h$ does so for domestic products affiliated to an international group and $\beta_1^h + \beta_3^h$ for foreign products not part of an international group. Finally $\beta_1^h + \beta_2^h + \beta_3^h + \beta_4^h$ shows pass-through for foreign affiliated with an international group. We calculate standard erros based on the Driscoll and Kraay (1998) variance estimator. In this way we correct the standard errors for the presence conditional heteroskedasticity, aribtrary spatial correlation and autocorrelation. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

Table C.16: Heterogeneity: Store size - Surface Area

Horizon	*Coef.*	$\hat{\beta}_i^h$	*p-value*	*N*	R^2
h = 0	i = 1	0.008***	0.0036	116,215	0.058
	i = 2	-0.003	0.4178		
h = 1	i = 1	0.046***	0.0000	111,102	0.126
	i = 2	0.003	0.5182		
h = 2	i = 1	0.087***	0.0005	106,428	0.198
	i = 2	0.002	0.7662		
h = 3	i = 1	0.106***	0.0008	101,860	0.252
	i = 2	0.007	0.5624		
h = 4	i = 1	0.140***	0.0005	97,373	0.292
	i = 2	0.026**	0.0260		
h = 5	i = 1	0.186***	0.0006	92,888	0.320
	i = 2	0.026*	0.0863		
h = 6	i = 1	0.239***	0.0002	88,463	0.336
	i = 2	0.034	0.2145		
h = 7	i = 1	0.277***	0.0003	84,211	0.342
	i = 2	0.041	0.3005		
h = 8	i = 1	0.295***	0.0005	80,010	0.352
	i = 2	0.047	0.3130		
h = 9	i = 1	0.288***	0.0008	75,848	0.368
	i = 2	0.052	0.3302		
h = 10	i = 1	0.314***	0.0008	71,729	0.391
	i = 2	0.063	0.2446		
h = 11	i = 1	0.406***	0.0029	67,669	0.415
	i = 2	0.060	0.3577		
h = 12	i = 1	0.382***	0.0003	63,626	0.439
	i = 2	0.065	0.2740		

Notes: This table presents the results after estimating equation 4 by seperating the monthly sample into two groups. We calculate standard erros based on the Driscoll and Kraay (1998) variance estimator. In this way we correct the standard errors for the presence conditional heteroskedasticity, aribtrary spatial correlation and autocorrelation with a lag length up to 13. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

Table C.17: Heterogeneity: Store size - Market Share

Horizon	*Coef.*	$\hat{\beta}_i^h$	*p-value*	*N*	R^2
h = 0	i = 1	0.006	0.1640	119,623	0.058
	i = 2	0.002	0.8214		
h = 1	i = 1	0.038***	0.0000	114,390	0.127
	i = 2	0.014	0.4529		
h = 2	i = 1	0.075***	0.0000	109,596	0.199
	i = 2	0.020	0.3204		
h = 3	i = 1	0.099***	0.0000	104,908	0.255
	i = 2	0.013	0.4776		
h = 4	i = 1	0.140***	0.0000	100,301	0.295
	i = 2	0.014	0.4788		
h = 5	i = 1	0.185***	0.0000	95,696	0.322
	i = 2	0.017	0.3725		
h = 6	i = 1	0.236***	0.0000	91,151	0.339
	i = 2	0.021*	0.0694		
h = 7	i = 1	0.274***	0.0001	86,779	0.346
	i = 2	0.025**	0.0346		
h = 8	i = 1	0.309***	0.0001	82,458	0.355
	i = 2	0.001	0.9760		
h = 9	i = 1	0.306***	0.0001	78,176	0.372
	i = 2	-0.004	0.8185		
h = 10	i = 1	0.334***	0.0002	73,937	0.395
	i = 2	-0.004	0.8453		
h = 11	i = 1	0.423***	0.0010	69,757	0.418
	i = 2	-0.004	0.8598		
h = 12	i = 1	0.411***	0.0001	65,594	0.442
	i = 2	-0.019	0.2687		

Notes: This table presents the results after estimating equation 4 by seperating the monthly sample into two groups. We calculate standard erros based on the Driscoll and Kraay (1998) variance estimator. In this way we correct the standard errors for the presence conditional heteroskedasticity, aribtrary spatial correlation and autocorrelation with a lag length up to 13. The reported significance levels are at the * 10%, ** 5% and *** 1% level.

Table C.18: Product categories matched with Harmonized System

Product category	*Category Description*	*HS code*
AFR	Air freshners	3303
BAR	Chocolate bars	180631
BDN	Baby drinks	2106
BEN	Baked beans	200559
BER	Beer	2203
BON	Candies	17049
BOU	Bouillon	201401
BUL	Chocolate	180632
CAS	Pralines	190510
CHV	Chocolate candies	1806
CIG	Cigarettes	2402
CNT	Sweet snacks	190532
COF	Coffee	90121
COL	Hair coloring products	3203
COO	Cookies	190531
CSP	Chocolate spread	180690
CUH	Fresh dairy products	40630
DBR	Draught beer	220300
DDS	Dessert and puddings	40291
DEO	Deodorant	330720
DES	Dessert and cakes	1905
DIN	Ready made meals	2106
DPH	Diapers	961900
DRG	Packed sweets	1806
DRN	Soft drinks	220210
DYR	Yoghurts	40310
ENG	Energy drinks	2202
EVP	Evaporated milk	40130
FCE	Facial care	330499
FDD	Dry baby food	402
FDW	Wet baby foot	200510
FML	Milk	40120
FWH	Face cleaning products	340130
GLZ	Candies	1905
GUM	Chewing gum	170410
HHC	Household cleaners	3402
INF	Infant milk	40291
INS	Insecticides	3808
ITE	Bottled ice tea	210120
JUI	Fruit and vegetable juices	2009
JUM	Yoghurtdrinks	40310
KFR	Cultered milk	40120

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Table C.18 – continued from previous page

Product category	*Category Description*	*HS code*
MLF	Liquid milk	40110
MRG	Margarine and butter	405
NDF	Dry noodles	190211
PS1	Dry pasta	190211
SAN	Sanitary protection	9619
SEA	Seasonings and herbs	91091
SHG	Shaving cream and cutters	330710
SHM	Shampoo	330510
SHW	Shower gels	330730
SNA	Salty snacks	1904
SOP	Sour cream	40150
SPP	Ready-made soups	210420
TBR	Toothbrushes	960321
TCL	Cleaning liquids	340220
TEA	Dried tea	992
TIS	Tissues	480300
TPR	Toilet paper	481800
TTH	Toothpaste	330610
VGC	Canned vegetables	2001
VOD	Vodka	220860
WTR	Mineral water	220110
YOS	Seperately sold yoghurt	40310

Notes: This table gives an overview on how the product categories observed in the dataset are matched with the Harmonized System on a 6-digit level. We use this matching table to obtain the import shares of Kazakhstan with respect to its trading partners for the different product categories in the dataset.