ESSAYS IN UNCONVENTIONAL MONETARY POLICY
AND FIRM DYNAMICS

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Abstract

This collection of essays uses microdata to investigate the effects of unconventional monetary policy and exchange rate shocks on the macroeconomy. Chapter 1 studies the transmission mechanisms of a prominent competitive devaluation in Japan and analyzes its effects on firm dynamics. The yen devaluation is shown to negatively affect exporters in terms of employment, domestic sales and market capitalization relative to their nonexporting peers. A New Keynesian general equilibrium model featuring common ingredients from international trade, including firm heterogeneity, varying intermediate import intensities, and international dollar pricing is constructed to explain the findings. Chapter 2 shows that banks’ exposure to large-scale asset purchases, as measured by the relative prevalence of mortgage-backed securities on their books, affects lending following unconventional monetary policy shocks. The chapter finds strong effects of the first and third round of quantitative easing (QE1 and QE3) on credit, with highly affected commercial banks increasing lending by 3% relative to their counterparts. QE2 had no significant impact, consistent with its exclusive focus on Treasuries sparsely held by banks. Overall, banks respond heterogeneously and the type of asset being targeted is central to QE. Chapter 3 uses a uniquely granular online retail dataset that spans Russia’s enormous currency depreciation in late 2014 to show that firms choose to offer lower quality products in response to rising input costs. This reallocation is not driven by an income shock or “flight from quality”. To explain quality downgrading, the chapter proposes a model of demand and firm dynamics where consumers value low prices and high qualities. It is argued that a positive correlation between marginal cost and quality can explain quality downgrading. The model is able to generate a reallocation in offerings towards low cost, low quality products, and yields starkly different welfare implications following an exchange rate shock than a model with only cost heterogeneity.
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To my wife, Yana, and my daughter, Anna.
Contents

Abstract iii
Acknowledgements iv
List of Tables ix
List of Figures x

1 (Un)Competitive Devaluations and Firm Dynamics: Evidence from Abe-
nomics 1

1.1 Introduction 1

1.1.1 Relation to the Literature 5

1.2 Abenomics 8

1.2.1 Institutional Background 9

1.2.2 Aggregate Patterns 11

1.3 Data and Empirical Results 13

1.3.1 Data Construction 13

1.3.2 Identification 15

1.3.3 Empirical Results 20

1.4 Model 26

1.4.1 Households 28

1.4.2 Firms 31

1.4.3 Asset markets and budget constraints 32

1.4.4 Wage Setting 34
List of Tables

<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Summary Statistics</td>
<td>58</td>
</tr>
<tr>
<td>1.2</td>
<td>Exporters versus Nonexporters</td>
<td>62</td>
</tr>
<tr>
<td>1.3</td>
<td>Mechanism</td>
<td>64</td>
</tr>
<tr>
<td>1.4</td>
<td>Mechanism in Calibrated Model</td>
<td>65</td>
</tr>
<tr>
<td>1.5</td>
<td>Calibration Values</td>
<td>67</td>
</tr>
<tr>
<td>1.6</td>
<td>Comparison of Models</td>
<td>67</td>
</tr>
<tr>
<td>2.1</td>
<td>Panel A: Summary Statistics (Call Reports)</td>
<td>83</td>
</tr>
<tr>
<td>2.2</td>
<td>Panel B: Summary Statistics (Dealscan)</td>
<td>83</td>
</tr>
<tr>
<td>2.3</td>
<td>Transition matrices</td>
<td>84</td>
</tr>
<tr>
<td>2.4</td>
<td>Correlation between Treatment and Initial Characteristics</td>
<td>86</td>
</tr>
<tr>
<td>2.5</td>
<td>Propensity Score Matching</td>
<td>87</td>
</tr>
<tr>
<td>2.6</td>
<td>Pooled QE Regression</td>
<td>91</td>
</tr>
<tr>
<td>2.7</td>
<td>Khwaja-Mian Estimator</td>
<td>98</td>
</tr>
<tr>
<td>2.8</td>
<td>Mechanisms</td>
<td>104</td>
</tr>
<tr>
<td>3.1</td>
<td>Parameters and moments</td>
<td>137</td>
</tr>
<tr>
<td>3.2</td>
<td>Structural demand parameter estimates</td>
<td>141</td>
</tr>
<tr>
<td>3.3</td>
<td>Reallocation towards low cost goods</td>
<td>144</td>
</tr>
<tr>
<td>3.4</td>
<td>Within-SKU Pass-through</td>
<td>155</td>
</tr>
</tbody>
</table>
List of Figures

1.1 Aggregate Quantities ................................................. 59
1.2 Aggregate Prices ..................................................... 60
1.3 Entry into Foreign Sales ........................................... 61
1.4 Cross-Sectional Results ............................................. 63
1.5 Mechanism .............................................................. 66
1.6 Mundell–Fleming ...................................................... 68
1.7 DCP with Heterogeneous Firms ................................. 69
1.8 Kimball with Heterogeneous Firms ......................... 70

2.1 MBS Prices

Note: Panel (a) shows the Fannie 30-year 3% Coupon MBS price series; Panel
(b) displays the Fannie 30-year 5% Coupon MBS price graph. Events related
to QE1, QE2, and QE3 are delineated by vertical red lines. .......... 82

2.2 Cross-Sectional Variation in MBS Holdings

Note: This figure shows a snapshot of the cross-sectional variation in MBS
holdings among banks in the main sample. The histogram plots densities
for the main treatment variable, the MBS-to-Assets ratio as of 2008Q1. For
reference, the MBS-to-Securities ratio in this period is also included. .... 85
2.3 Quantitative Easing & Bank Lending

Note: This figure displays the Federal Reserve Holdings of U.S. Treasuries and Mortgage-Backed Securities from 2008Q1 until 2014Q1, all measured on the left vertical axis in USD millions. It also shows the average lending-to-assets ratios for banks within the highest 25% of MBS-to-Assets holdings versus the lowest 25%. Lending is measured on the right vertical axis. The vertical dashed lines and shaded areas mark the QE1, QE2 and QE3 periods, respectively.

2.4 All Banks – coefficient plots

Note: These figures plot the estimated $\delta_t$ coefficients of equation 2.2 with 95% confidence intervals around them. Time is measured on a quarterly level and the vertical vermillion (dot-dashed), light-blue (dashed) and turquoise (long-dashed) lines mark the QE1, QE2 and QE3 episodes, respectively.

2.5 Small versus Large Banks – coefficient plots

Note: These figures plot the estimated $\delta_t$ coefficients of equation 2.2 for small and large banks with 95% confidence intervals around them. Time is measured on a quarterly level and the vertical vermillion (dot-dashed), light-blue (dashed) and turquoise (long-dashed) lines mark the QE1, QE2 and QE3 episodes, respectively.

2.6 Placebo tests – coefficient plots

Note: These figures plot the estimated $\delta_t$ coefficients of equation 2.2 with 95% confidence intervals around them for the period from 2001Q2 to 2004Q4. Time is measured on a quarterly level and the vertical vermillion dashed line marks the beginning of the post-2001 economic boom.
2.7 Mechanisms: Net Worth

Note: This figure displays the average growth of bank net worth around QE1 (between vertical vermillion dash-dotted lines), QE2 (between light-blue dashed lines) and QE3 (right of turquoise vertical long-dashed line). Banks in the treatment group belong to the upper quartile of the MBS-to-Assets distribution in 2008Q1, while banks in the control group belong to the lower quartile.

2.8 Mechanisms: Realized and Unrealized Gains

Note: Panels (a) and (b) display the average net realized and unrealized gains (or losses) on securities as a fraction of equity around QE1 (red vertical line), respectively. Panels (c) and (d) plot the corresponding figures around QE3. Banks in the treatment group belong to the upper quartile of the MBS-to-Assets distribution in 2008Q1, while banks in the control group belong to the lower quartile.

3.1 Small, positive relationship between cost and quality

3.2 Overlapping Generations of Goods

3.3 Cost of Goods Sold

3.4 Price Indexes

3.5 Price Adjustments

3.6 Fabrics & Quality Index

3.7 Demand Channel
Chapter 1

(Un)Competitive Devaluations and Firm Dynamics: Evidence from Abenomics

1.1 Introduction

How are monetary policy shocks transmitted in open economies, and how do they affect firm dynamics? Are competitive devaluations effective in helping countries pursue export-led expansions in the face of increasingly complex global supply chains? Competitive devaluations, or currency wars, are said to occur when a country eases monetary policy specifically to depreciate its exchange rate, with the ultimate objective of making its exports relatively cheap and gaining a competitive advantage in international trade. Yet despite such competitive devaluations being a major part of policy discourse, I show that their usually assumed transmission mechanism is at odds with microdata as well as the evolution of net exports and inflation.

A version of this paper was previously presented at the University of Cambridge, Columbia GSB, Harvard Business School, London Business School, MIT Sloan, Princeton University, and University of Virginia.
This paper considers a recent devaluation episode in Japan to empirically dissect the mechanisms underlying competitive devaluations and develops a theoretical framework to analyze the effects of such exchange rate policies on firm dynamics. Manipulation of the exchange rate to gain a competitive advantage over a country’s trading partners has been recognized as a significant danger to the stability of the international monetary system since Bretton Woods. Institutions and rules have been established to explicitly prevent countries from resorting to beggar-thy-neighbor devaluation spirals. Such concerns were strong during the Asian crises in the late 1990s as well as following the financial crisis of 2008, once recovery was underway and national economic interests began to diverge. Some emerging-market policymakers famously argued that the Fed’s aggressive unconventional monetary policy measures were detrimental to other economies.\(^2\) Indeed, in the new open economy macroeconomics literature, as in the traditional Mundell–Fleming–Dornbusch model, positive monetary shocks increase domestic output, employment and depreciate the real exchange rate, thereby improving the trade balance as expenditure switches toward domestic exports.

The central identification challenge associated with estimating the impact of competitive devaluations on firm dynamics is that exchange rate movements are seldom exogenous. For instance, the emerging-market devaluations of the late 1990s were attributed either to sudden stops or major crises (e.g., Argentina 2001–2002). This paper, however, argues that post-2012 Japan offers a unique natural experiment for studying competitive devaluations. Firstly, Japan’s currency devaluation was a novel policy response to persisting economic problems, allowing one to examine the aggregate reaction and estimate its effects on firm dynamics through the use of microdata. Secondly, the devaluation stands out from previous episodes with regard to its magnitude and nature: after the yen reached postwar highs against the U.S. dollar in 2012, it then weakened by a staggering 50% within two years. That devaluation had, arguably, been driven by purely monetary factors and did not come about as a result of adverse productivity shocks that led to a collapse in GDP or the dollar value.

of imports, as was the case with many emerging-market economies. More precisely, to raise inflation, stimulate growth, and weaken the yen following years of relatively timid monetary interventions, the new prime minister, Shinzo Abe, proposed three arrows of what has come to be known as Abenomics: monetary stimulus, fiscal flexibility, and structural reform.

The empirical strategy in this paper begins with a close examination of the effects stemming from that experiment and its most potent weapon: unconventional monetary policy. And while the Bank of Japan (BoJ) more than doubled its balance sheet from 2013 to 2015, prevailing views contend that none of the other arrows were successful. Japan’s public debt looks as bad as ever despite an increase in the consumption tax in 2014, and almost nothing has been done in such areas as labor-market reform. Those background details constitute the foundation of a two-layered identification strategy: (1) at the micro level, firms differ in their exposure to exchange rate fluctuations, whereas (2) at the macro level, Abenomics was a new monetary policy initiative targeting long-term problems. The episode is, therefore, a highly suitable laboratory for studying how competitive devaluations influence firms and aggregate outcomes.

I find that the large yen depreciation resulted in purely domestic firms, in other words, those catering exclusively to home markets, expanding more than exporters in terms of overall home sales (by 15%), employment (by 6%), and stock market capitalization (by 10%). Meanwhile, and similarly in sharp contrast to the predictions of standard open economy macro models, aggregate output and consumption reacted sluggishly to the monetary stimulus and subsequent currency depreciation while the trade balance even deteriorated. The feeble response of Japanese exporters, which are the country’s largest and most productive companies, suggests that the gains in total sales and employment among purely domestic firms entail a reallocation of resources away from exporters and toward less productive enterprises. Furthermore, all of the main results hold within and not just across industries, and the patterns are strongest in sectors that are more reliant on imported intermediate in-

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puts. Taken together, these findings point to an underappreciated mechanism of competitive devaluations: consistent with previous work on exchange rate pass-through into prices using trade data (Amiti et al. (2014)), exporters tend to simultaneously be the largest importers and thus their expansion may be hampered by offsetting exchange rate movements on the marginal cost side.

Motivated by these empirical findings, the paper develops a two-country New Keynesian general equilibrium model of a monopolistically competitive industry that incorporates accepted ingredients from international trade to understand the mechanisms driving the main cross-sectional results and analyze the effects of monetary policy in open economies. Households derive utility from a composite consumption good and leisure, and are also specialized in one type of labor, which they supply monopolistically. Workers set next period’s nominal wages (in their domestic currency) in advance of production and consumption. To the best of my knowledge, the framework in this paper is the first to combine heterogeneity among firms (in the spirit of Melitz (2003)), imported intermediate inputs (as in Halpern et al. (2015)), and international dollar pricing (Gopinath et al. (2010) and Gopinath (Forthcoming)) to analyze the effects of competitive devaluations on firm dynamics. More productive companies end up sourcing a larger amount of their inputs from abroad, which is a consequence of the intermediate input aggregator in the production function displaying a “love of variety” feature, with inputs being imperfectly substitutable as in Ethier (1982). The framework is then used to analyze the implications of an imported input cost shock on aggregate consumption, prices, and firm-level outcome patterns.

The model is calibrated to match the empirical regularities for Japan using standard parameters, and simulations are run to evaluate quantitatively the combined impact of firm heterogeneity and dollar pricing relative to standard models that assume away these channels. The effects of competitive devaluations on firms’ relative profitability, consumption, and employment allocations are considered following nominal exchange rate devaluations for an economy with or without firm heterogeneity, assuming different price setting rules and for
varying import intensities. The quantitative results manage to reproduce the main patterns in the microdata, with international dollar pricing being the central mechanism generating a muted response of exports. Furthermore, because exporters tend to be the largest importers, they become forced to raise prices at home relative to less productive nonexporting firms which remain relatively unexposed to the cost shock. Without changing the qualitative predictions of the model, the quantitative fit of these relative adjustment patterns is much improved via the addition of strategic complementarities in firm price setting.

While a standard New Keynesian framework with producer currency pricing, homogeneous firms, and no import intensities, as in the traditional Mundell–Fleming case, predicts that net exports to pre-shock GDP and inflation should increase by around 4% and 1%, respectively, the benchmark model matches these aggregate moments with much greater success, suggesting a fall in the trade balance to pre-shock GDP ratio of about 1% and an increase in CPI of 3%. Counterfactual simulations suggest vastly heterogeneous aggregate consequences depending on a country’s prevalent import intensity distribution, and they underscore how the U.S. benefits from the international role of the dollar not just through its own monetary policy spillovers but also as a result of greater insulation from nominal devaluations undertaken abroad. Contrary to much of the conventional wisdom, the new paradigm conceived in this paper highlights the role of import substitution—rather than the development of national export champions—as the key transmission mechanism in the wake of competitive devaluations.

1.1.1 Relation to the Literature

This research is related to the new open economy macroeconomics literature. The first generation of contributions to this field has emphasized welfare and policy implications of monopoly distortions in production, extending to an open-economy setting key conclusions of influential closed-economy models such as Blanchard and Kiyotaki (1987) and Ball and Romer (1990). In those models wages and prices are suboptimally high while output and
consumption are low. Obstfeld and Rogoff (1995) then developed a two-country model to think about global macroeconomic dynamics in an environment with monopolistic competition and sticky nominal prices. The model developed in this paper is close in spirit to the Obstfeld and Rogoff (2000) framework based on sticky nominal wages. Corsetti et al. (2000) develop a general equilibrium model with monopolistic competition and nominal rigidities to study the impact of a devaluation by one country on its trading partners and find that neighboring economies may benefit from an improvement in their terms of trade. Corsetti et al. (2010) study optimal monetary stabilization policy in interdependent open economies by proposing a unified analytical framework that systematizes the existing literature. Even if the mechanisms under consideration are completely distinct, the results in the present study are similar in spirit to Corsetti and Pesenti (2001), who find that an unanticipated exchange rate depreciation can be beggar-thyself rather than beggar-thy-neighbor as gains in domestic output are offset by deteriorating terms of trade. The monetary block in the paper is close to the modeling choices in Kehoe and Midrigan (2007), while a central ingredient generating the results is international dollar currency pricing as presented in Gopinath et al. (2010), Gopinath (Forthcoming) and modeled in Casas et al. (2016).

This paper also speaks to the literature on competitive devaluations and exchange rate policy. Caballero et al. (2016) explore the effects of extremely low equilibrium real interest rates in a world with integrated but heterogeneous capital markets and nominal rigidities and find that competitive devaluations provide stimulus for the undertaking country at the expense of other countries. Another contemporaneous paper by Eggertsson et al. (2016) finds that exchange rates have powerful effects when the economy is in a global liquidity trap. Caballero and Lorenzoni (2014) model the need for intervention in the foreign exchange market to protect the export sector following periods of currency appreciation; Itskhoki and Moll (2015) study active development, exchange rate and industrial policies in a standard growth model with financial frictions; Rodrik (2008) shows that undervaluation of the currency stimulates economic growth; Bergin and Corsetti (2016) develop a two-country New Keynesian...
model with one perfectly and another monopolistic competitive sector to show that monetary policy can foster investment and entry into the differentiated goods sector; Alessandria et al. (2015) explore the source and aggregate consequences of the gradual export expansion in emerging markets following large devaluations; Burstein et al. (2005) argue that the primary force behind the large drop in real exchange rates that occurs after large devaluations is the slow adjustment in the price of nontradable goods and services; and Drenik (2015) shows that sectoral labor markets can respond differently under various exchange rate regimes and that exchange rate policy can have redistributive effects.

The paper is further related to numerous works on international trade and pass-through. In a seminal contribution, Melitz (2003) develops a trade model with heterogeneous firms to analyze the intra-industry effects of international trade. Atkeson and Burstein (2008) build a model of imperfect competition and variable markups to explain the main features of fluctuations in international relative prices. Similar to the mechanism in this paper, Mendoza and Yue (2012) show that imported inputs require working-capital financing and that efficiency losses result when those inputs are replaced by imperfect substitutes. Halpern et al. (2015) estimate a model of importers in Hungarian microdata and find large effects from imported inputs on firm productivity. Amiti et al. (2014) show that large exporters are simultaneously large importers, and they stress the importance of this fact for understanding low aggregate exchange rate pass-through, whereas Amiti et al. (2016) use a similar framework to estimate strategic complementarities in price setting across firms. Benigno and Fornaro (2012) argue that firms in the tradable sector absorb foreign knowledge by importing intermediate inputs, and Dekle et al. (2014) build a dynamic general equilibrium model with heterogeneous firms to reconcile the disconnect between exchange rate movements and net exports. Looking at firm-level reactions to exchange rate shocks and equipped with trade data, Gopinath and Neiman (2014) find that import demand is non-homothetic and the implications for productivity depend on the details of individual firm adjustments that cannot be summarized by changes in the aggregate import share.
Finally, a range of studies have linked firm profits to large devaluations by combining
tools from macroeconomics and the corporate finance literature. Gorodnichenko and Weber
(2016) show that in the aftermath of monetary shocks, the conditional volatility of stock
market returns rises more for companies with stickier prices than for firms with more flexible
price setting rules. Griffin and Stulz (2001) explore the presence of economically significant
competitive effects of exchange rate shocks on firms’ stock prices. Aguiar (2005) shows
that firms with heavy exposure to short-term foreign currency debt before the Mexican
devaluation in 1994 experienced relatively low levels of post-devaluation investment. Desai
et al. (2008) find that U.S. multinational companies increase sales, assets, and investment
significantly more than local firms following depreciations. Hofmann et al. (2016) explore
sovereign yields and the risk-taking channel of currency appreciation. The empirical methods
of this paper as well as the focus on firm-level sales (or market shares) and profitability
measures are in the spirit of previous corporate finance work that studied product market
outcomes across industries (Giroud and Mueller (2011), Fresard (2010)).

The structure of this paper is as follows. Section 3.2.2 begins with a chronology of the
main events around Abenomics and lays out institutional background details in post-2012
Japan. Next, section 3.2 describes the data sources, presents the identification strategy, and
walks through the central empirical results. Section 1.4 develops a theoretical framework to
analyze competitive devaluations featuring well-known ingredients from international trade
that have so far been left out in the analysis of monetary policy. Section 1.5 numerically
evaluates the impact of competitive devaluations on firm dynamics and aggregate patterns.
Section 3.8 concludes.

1.2 Abenomics

This section describes the institutional background in Japan and offers a chronology of
Abenomics alongside relevant aggregate trends for output and inflation following the inter-
ventions. It is argued that the episode constitutes a particularly clean example of a recent competitive devaluation and is, therefore, an ideal laboratory for studying the dynamic adjustment paths of the Japanese economy.

1.2.1 Institutional Background

Having fought deflation for more than two decades after the asset price bubble burst in 1991, Japan remains plagued by weak growth and feeble consumer sentiment despite countless attempts to revitalize its economy. Short-term nominal interest rates have hovered around to zero since the mid 1990s, meaning that conventional monetary policy measures have long exhausted their potential, and in spite of a mild economic recovery in the 2000s along with various fiscal stimulus programs, aggregate consumption and investment figures remain subdued. It is against that backdrop of perpetual malaise that shortly after taking office in December 2012, Japan’s new prime minister, Shinzo Abe, announced ambitious plans for a novel array of unorthodox policies aimed at breaking through Japan’s seemingly unending deflationary spiral.

Abe’s approach, soon labeled Abenomics, consisted of three pillars and was meant to combine aggressive monetary easing with fiscal policy and structural reforms. Its immediate goal was to boost domestic demand and growth while raising inflation to a newly set target of 2 percent. Abe’s less-well-implemented structural policies were also meant to improve the country’s economic performance by increasing competition, overhauling corporate governance, making labor markets more flexible, and cementing trade partnerships.

The first, and central, arrow of Abenomics was an unprecedented policy of monetary easing. Soon after Abe’s election, the Bank of Japan (BoJ) was given a mandate to generate 2 percent inflation as measured by the consumer price index (CPI), while the introduction of so-called quantitative and qualitative monetary easing (QQE) prescribed money market operations such that the monetary base would increase at an annual pace of about 60-70 trillion yen. This meant that high-powered money reached approximately 200 trillion yen
at the end of 2013 and 270 trillion yen at the end of 2014, starting from 138 trillion yen outstanding at the end of 2012. In this process, the BoJ began buying Japanese government bonds (JGBs), increasing their outstanding amount at an annual pace of about 50 trillion yen, and JGBs of all maturities, including 40-year bonds, were made eligible for purchase. With the objective of lowering risk premia, the BoJ also started purchasing ETFs and Japan’s real estate investment trusts (J-REITs) on a much smaller scale, with annual paces of 1 trillion yen and 30 billion yen, respectively.

Yet, as Japan’s economy continued to recover moderately and inflation remained subdued following a consumption-tax hike and a substantial decline in crude oil prices, the BoJ voted for an acceleration of its JGB purchases on October 31, 2014. As a result, the amount outstanding of JGBs would now increase at an annual pace of about 80 trillion yen (an addition of about 30 trillion yen compared with the first round). The average remaining maturity of the BoJ’s JGB purchases was also extended to about 7-10 years. Overall, and compared with past efforts to revive Japan, this monetary component of Abenomics achieved a great deal by beating core deflation (excluding energy prices) and devaluing the yen by 50% in just under two years.

In the meantime, structural reforms and fiscal policies are seen to have advanced haltingly. An increase in the consumption tax from 5% to 8% in April 2014 caused heavy and lasting damage to household spending and GDP growth despite an initial fiscal stimulus bill of 10.3 trillion yen targeting disaster prevention, spending on infrastructure, and reconstruction. A second value-added tax rise to 10% has been announced and twice postponed. Essentially, with a public debt level of 250%, Japan’s ability to use expansionary fiscal policy is limited by the important challenge of fiscal consolidation. Consistent with the main identifying assumptions employed in this paper, Krugman has recently argued that Japanese growth has been disappointing due to the missing second and third arrows. In fact, a recent IMF
estimate says fiscal policy has actually gotten tighter due to the described consumption-tax increase.

More precisely, Abe’s efforts at structural reforms failed to deliver any substantial breakthroughs that could spur economic growth. The few adopted policies, implemented against the will of the country’s powerful business lobby, obliged shareholders to be more assertive and introduced new codes on corporate governance for Japanese institutional investors. In 2012, only two-fifths of leading companies had independent directors, whereas nearly all of them do now. And even though progress has been incremental, these are positive moves that may have propelled firms’ equity prices and raised consumer confidence. Overall, however, structural reforms remain largely unimplemented, and unconventional monetary policy is unanimously seen as the most potent arrow of Abenomics (Hausman and Wieland (2015)).

1.2.2 Aggregate Patterns

Panel (a) of Figure 3.3 displays the Japanese nominal exchange rate as well as the trade balance over time. As the yen began to devalue rapidly against most of Japan’s trading partners’ currencies at the end of 2012, neither exports nor imports appeared to react for around two years, until the second wave of QQE further depreciated the yen and appeared to be gradually putting a dent into the growth of imports. Exports, however, still failed to increase, as would be suggested by commonly accepted macroeconomic theory and intuition. Notably, that weak response of the trade balance, which started to improve only around 2015 is not simply the standard J-curve effect. Even though it is true that Japanese firms seemed reluctant to drop their imports for a very long time, suggesting low substitutability between domestic and imported intermediate inputs, classic open economy reasoning would dictate that exports should eventually create a positive trade balance dynamic. But the competitive devaluation in Japan suggests a starkly different pattern: exports remained almost completely insensitive to the relative price of domestic currency. Moreover, those

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patterns are at odds with the well-known local currency pricing (LCP) paradigm because one would not expect to see imports increase anywhere as much under this particular form of price rigidity.

[Insert Figures 3.3 and 3.4 here]

Panel (b) of Figure 3.3 shows the growth of real GDP and household consumption expenditure from 2010 until 2015. The vertical red line delineates the post-QQE period and shows the remarkably slow output and even negative consumption growth after 2013. And although this may be partially the result of an increase in the value-added tax in 2014, these trends are completely at odds with predictions of New Keynesian models following an aggressive monetary expansion. Figure 3.4 presents evidence on the reaction of aggregate prices and wages. Panel (a) shows that the price of tradables increases in yen after the devaluation. The increase of the import price index is particularly pronounced, as would be consistent with international dollar pricing. The consumer price index (CPI) barely moved following the monetary expansion, rising by only about 3% two years after the devaluation started. This comes despite a 50% nominal devaluation but is only partially surprising given that Japan is a fairly closed economy: exports and imports each represent about 14% of GDP, respectively. A potential source of much of the observed price rigidity could be nominal wage stickiness. Indeed, Panel (b) of Figure 3.4 displays both the nominal and real wage indexes for Japan over this time period and suggests the assumption of sticky wages to be well-founded: nominal wages are largely fixed, whereas the real wage index declines by exactly the same amount that overall inflation increases. Those aggregate patterns show that both sticky wages and international dollar currency pricing seem to be key features of the macroeconomic environment in Japan, an observation that will inform modeling choices in section 1.4. Next, microdata will be put to use to shed more light on the dynamic adjustment paths of the Japanese economy following the large-scale monetary policy intervention.
1.3 Data and Empirical Results

This section describes the microdata, frames the identification challenges, and presents key empirical results together with the methodology used for exploring the relative expansion paths of nonexporting and multinational firms during Abenomics.

1.3.1 Data Construction

The operating and financial information on Japanese firms and their international sales is sourced from the Worldscope, Capital IQ, and ORBIS data sets together with their segment files. The former two sources mostly cover bigger listed companies, and they are combined primarily for cross-checking reasons and to minimize the number of missing observations. The ORBIS database, compiled by Bureau van Dijk Electronic Publishing (BvD), also provides firm-level microdata for many countries around the world and contains financial accounting information from detailed, harmonized balance sheets and income statements of almost exclusively private companies. As a result, the main sample contains annual firm-level data on public Worldscope and Capital IQ, as well as private ORBIS firms over the period from 2007 to 2015.

All main specifications restrict attention to a balanced sample, and firm-years for which information on sales, employment, and total assets is not available are excluded from the analysis. Observations with negative equity, sales, or sales growth larger than 200% are similarly omitted. Product markets (industries) are classified at the four-digit SIC level and all financial firms (6000–6800 SIC range) are dropped. In the Worldscope and Capital IQ subsample, this selection procedure leaves 431 four-digit industries and 1,811 companies operating mainly in manufacturing sectors. Together with the ORBIS data set, this adjustment procedure leads to a total of 619 four-digit industries and 33,541 firms. Based on those data, the average number of firms per industry is about 54, and the number of companies with multinational operations and exports constitutes about 10% of the total number of firms.
in an industry. Appendix 2.7 provides more complete definitions of the variables used in the empirical section as well as well-known techniques to avoid missing-data problems when downloading the ORBIS data. Overall, the preparation of the data follows standard adjustment procedures found in much of the corporate finance literature (e.g., Campello (2006) and Bates et al. (2009)).

Even though many of the empirical tests in this paper pool both public and private companies, Japan is known to have one of the highest percentages of publicly listed firms relative to GDP even when compared against other developed nations. This means that confining all of the analysis to the subsample of only listed firms does not change any of the main results, and it enables one to analyze the reaction of additional outcome variables, such as stock market prices. Many investors and market participants have further noted the relatively strong performance of small-caps in Japan, even when judged against some of the biggest exporters since the onset of Abenomics. Given that the largest exporters are usually also the largest importers (Amiti et al. (2014)), this preliminary evidence lends additional support to the main intermediate inputs channel studied in this paper.

Table 1.1 provides summary statistics on a range of key firm-specific characteristics in 2012, one year prior to the onset of Abenomics. Panel (a) focuses on the subsample of public firms, mostly listed on the Tokyo Stock Exchange. The variable “domestic” will be similar to the key treatment indicator, equal to 1 whenever the firm has no foreign sales during the whole sample period. With a mean value of 0.57 and a median of 1, the number of exporters is quite high even if most of the listed companies are still found to be catering exclusively to the home market. Public companies have relatively large balance sheets (size) and employment numbers, especially when compared with Japanese private firms in Panel 5

5 According to the World Bank, the market capitalization of listed domestic companies in Japan as a percentage of GDP was about 119% in 2015, whereas the same number for Germany stood at 51.1%.

6 Source: “Japan’s small-caps doing well while big exporters get a bruising”, Japan Times, Jan 15, 2016.

7 The analysis relies on the segment files to identify exporting and nonexporting firms. Whereas, in principle, foreign sales combine exports with total sales generated in other countries, extant trade research points to most international commerce as carried out by multinational firms that both export and use their foreign affiliates to serve the host market (e.g., Rob and Vettas (2003), Tintelnot (2016)).
Public firms are also substantially older than their private counterparts, with the mean age being 58.56 years for the former and 33.17 years for the latter group. In general, there is ample heterogeneity in financial conditions as well as sufficient variation in firm’s export status. In fact, exporters on average capture 60% of the total domestic sales volume from 2010 to 2015.

The aggregate data on output, inflation, trade balance, and interest rate statistics is collected from the Japanese Ministry of Finance and the Bank of Japan. Spot and forward exchange rate information is sourced from IHS Global Insight, and the import content of production is measured at a relatively aggregated industry level, based on the 2011 OECD input-output table statistics for Japan. The observed variation in import intensities across sectors is exploited to shed more light on the precise mechanisms underlying all of the key cross-sectional firm-level results.

1.3.2 Identification

This section lays out the paper’s main identification strategy for estimating the adjustment paths of relatively exposed versus unexposed firms by using microdata. Methods for gauging the importance of different mechanisms are similarly discussed.

The central identification challenge with estimating the impact of competitive devaluations on firm dynamics is the endogeneity of nominal exchange rate movements. Many countries have experienced periods of large real exchange rate devaluations, and in general many factors have the potential to fuel such currency fluctuations. For example, those factors can stem from domestic policies aimed at combating deflationary risks, to large capital outflows caused by domestic or external factors, to exchange rate interventions at home or abroad, to domestic consumption booms, or to a sharp fall in the terms of trade in commodity producing economies.
Meanwhile, the Japanese exchange rate devaluation from late 2012 until 2014 was a new policy response to persistent issues. The Japanese experience is a fitting laboratory for studying competitive devaluations for two additional reasons: its magnitude—with the yen depreciating by about 50% against the U.S. dollar within just two years—and the fact that monetary forces were primarily behind the movement. Attributing any potential findings to a competitive devaluation would be complicated if, for example, adverse productivity shocks were the true underlying forces.

This paper’s empirical strategy is hence to look at the impact of this monetary policy experiment through the use of microdata and to exploit Japan’s institutional background details in setting up a two-layered identification strategy: at the micro level, firms differ in their exposures to exchange rate fluctuations, whereas at the macro level, Abenomics was a new monetary policy initiative targeting long-term problems.

Cross-sectional Evidence

Much of the evidence relies on the nominal exchange rate affecting nonexporting companies differentially compared with Japanese multinationals. Because the objective is to understand the transmission mechanism of competitive devaluations by using firm-level data, the main focus will be on investigating the causal impact of the yen devaluation on domestic sales, employment, and market capitalization via a difference-in-differences (DinD) estimation strategy.

Another important concern has to do with the timing of the effects. In particular, any differences between the more affected exporters and the relatively unaffected, purely domestic firms might be driven by certain pre-existing trends that originated before the onset of Japan’s aggressive monetary stimulus. To lend additional support to the causal interpretation of the results, the next series of tests relies on using repeated observations for the same company over time. The following fixed-effects regression allows one to see whether causes
happen before consequences and not vice versa:

\[
\log(Y_{i,t}) = \alpha_i + \theta'X_{i,t-1} + \sum_t \gamma_t D_t + \sum_t \delta_t (D_t \cdot X_{i,t-1}) + \sum_t \psi_t (D_t \cdot \text{Treat}_i) + \epsilon_{i,t} \quad (1.1)
\]

\[
\forall i, \forall t \in \{2010, \ldots, 2015\} \setminus \{2012\}
\]

where \(Y_{i,t}\) are either domestic sales, total employment, or market capitalization of company \(i\) in year \(t\), \(\alpha_i\) are firm fixed effects, \(\text{Treat}_i\) is an indicator variable equal to 1 whenever a firm is a Japanese exporter and 0 when the firm is entirely domestic, \(D_t\) is an indicator for the time period (year), with 2012 taken as the omitted category, \((D_t \cdot \text{Treat}_i)\) represents an interaction term between the year dummies and the treatment indicator defined by the disparity between solely domestic versus exporting firms, and \(X_{i,t-1}\) is a matrix of control variables that includes lagged size (log of assets), leverage, the market-to-book ratio (for public firms), as well as cash-to-assets, which are accounting control variables widely used in the corporate finance literature. All standard errors are clustered at the firm-level to allow for serial correlation across time.

As required with any difference-in-differences estimation approach, this specification also provides evidence on the parallel trends assumption in all outcome variables. That is, in the absence of treatment, the unobserved disparities between exposed and less exposed companies should be constant over time; the validity of the estimation procedure relies on outcome variables that would have continued to develop as they did before the competitive devaluation of the yen. Unless this assumption is valid, the estimated treatment effects would be biased versions of the true impact. As an additional robustness check on the identification strategy, all control variables are interacted with the \(D_t\) indicators to allow for possible heterogeneous reactions to the monetary expansion across different types of firms. For example, a prominent alternative hypothesis involves simultaneous interest rate changes that occurred as a consequence of QQE, yet even if movements in interest rates had nonuniform repercussions
for exporters and solely domestic firms, the interaction of all control variables, especially leverage, with the full set of year dummies would soak up the bulk of that variation.

The main parameters of interest are the $\psi_t$ because they capture the difference between more strongly affected exporters and less affected purely domestic firms over time. The estimated fixed-effects model includes leads going back to 2010 and lags reaching 2015. The specification allows for any causal direction of the findings and assesses whether the effects grow or fade over time.

**Mechanisms**

Previous literature has established the centrality of imported intermediate inputs to the production processes of large exporting firms (Amiti et al. (2014)). Despite the lack of access to firm-level trade data, which would allow for the exploration of the importance of this channel directly, insights into the driving forces behind the growth (or contraction) of exporters relative to nonexporters in Japan following Abenomics can be gained by using a triple difference (DDD) identification strategy.

In particular, manufacturing and non-financial industries are known to be heterogeneously reliant on imported intermediate inputs in their production. As a result, one should expect to see more pronounced differences across all-time exporters and solely domestic firms in sectors that are more dependent on imported intermediate inputs than industries, which are not. Assuming that exporters are also the biggest importers (as documented by Amiti et al. (2014)), disparities between both groups of firms are bound to be particularly stark in sectors in which exporters are highly exposed to changing input prices rather than industries where almost all factors of production are obtained domestically. That reasoning motivates the following triple difference specification:

$$
\log(Y_{i,t}) = \alpha_i + \alpha_1 X_{i,t-1} + \alpha_2 (X_{i,t-1} \cdot QE_t) + \beta_1 (Treat_i \cdot QE_t) + \beta_2 (IC_j \cdot QE_t) + \gamma (Treat_i \cdot IC_j \cdot QE_t) + \nu_{i,t}
$$

(1.2)
where, as earlier, $Y_{it}$ are either domestic sales, total employment, or market capitalization of company $i$ in year $t$, $\alpha_i$ are firm fixed effects, $X_{i,t-1}$ is a matrix of control variables that includes lagged size, leverage, the market-to-book ratio (for public firms), as well as cash-to-assets, $Treat_i$ is an indicator variable equal to 1 whenever a firm is a Japanese exporter and 0 when the firm is entirely domestic, $QE_t$ is an indicator equal to zero in 2012 before Abenomics and unity after Abenomics in either 2014 or 2015, and $IC_j$ is the import content of production across various industries based on Japan’s 2011 input-output tables. An attractive feature of this input-output table measure is that it allows one to compute the value of imported inputs used indirectly in production of a good. That is, imported inputs may be used in one sector, whose outputs are employed in another sector, then a third, and eventually become embodied in a final good. Note that the terms $Treat_i$, $IC_j$, and $Treat_i \cdot IC_j$ are not explicitly thrown into the regression because of the inclusion of firm fixed effects. All standard errors are clustered at the firm-level to allow for serial correlation across time.

The coefficient of interest is $\gamma$ as it captures the percentage change in the respective outcome variable after Abenomics for exporting or nonexporting firms in import reliant versus less import dependent sectors. A positive coefficient would imply that, ceteris paribus, the Japan’s competitive devaluation leads to a stronger expansion of exporters relative to solely domestic firms in sectors that are more exposed to importing.

This triple difference methodology is applied to the pooled sample of private and public firms, and it is further extended to emulate regression 1.1 in accounting for the timing of

\[ IC_i = \frac{u' A_m (I - A_d)^{-1} q}{q_i}, \]

where $A_d$ and $A_m$ are input-output coefficient matrices, $q$ is the consumption vector for each sector, $q_i$ is total consumption for country $i$, and $u$ is a vector of ones. For sector $j$, the imported input share of gross output can be obtained from the individual columns of matrix $u' A_m (I - A_d)$.

\[ ^{8} \text{This number represents the degree of vertical specialization and measures the contribution that imports make in the production of goods in a certain industry. It is calculated as follows for country } i: \]

\[ ^{9} \text{In the end, the core results are insensitive to using the direct or indirect measure of import dependence since the ranking between industries remains completely unaltered with either approach.} \]
any effects. That is, the following fixed-effects equation is estimated and allows one to
test whether the gaps between exporters and nonexporters widen after the introduction of
Abenomics rather than before:

\[
\log(Y_{i,t}) = \alpha_i + \theta'X_{i,t-1} + \sum_t \gamma_t D_t + \sum_t \delta_t (D_t \cdot X_{i,t-1}) + \sum_t \psi_t (D_t \cdot Treat_i) \\
+ \sum_t \lambda_t (D_t \cdot IC_j) + \sum_t \zeta_t (D_t \cdot Treat_i \cdot IC_j) + \epsilon_{i,t}
\]

\(\forall i, \forall t \in \{2010, \ldots, 2015\} \setminus \{2012\}\)

where all of the main variables and interaction terms are as before, and the standard errors
are clustered at the firm-level to allow for serial correlation across time. The only novelty is
that now the parameters of interest are \(\zeta_t\), as they measure the difference between exporters
and purely domestic firms over time in more versus less import reliant industries. This
regression tests if the effects grow or fade over time and provides evidence of the validity of
the critical parallel trends assumption.

1.3.3 Empirical Results

This section uses microdata to analyze how Japan’s economy reacted to the devaluation
and presents the main cross-sectional findings on the relative growth of exporters versus
nonexporters, delving into the evidence on the potential mechanisms underlying all results.
Heterogeneous import intensities are explored as the key driving forces behind the nonuni-
form adjustment patterns across firms.

Entry into Foreign Sales

Before a comparison of the response of exporting and purely domestic enterprises with
Japan’s competitive devaluation over time, the data reveal some useful information about
entry into foreign sales. Whereas Panel (a) of Figure 3.3 clearly documented a weak reaction
of export volumes in the aggregate, the weaker yen still appears to have induced a higher level of participation in foreign sales across companies at the micro-level.

Panel (a) of Figure 1.3 displays the fraction of firms with foreign sales in the whole sample of public and private firms over time. The nominal exchange rate seems to clearly lead a steep increase in the proportion of companies with positive foreign sales. However, the evidence in Panel (b) of Figure 1.3 shows that, despite growing at faster rates than existing multinationals, the cohort of 2013 entrants (firms that have never listed any foreign sales prior to 2013) represents only a negligible fraction of total foreign sales volume in the sample. Indeed, newcomers turn out to resemble purely domestic public firms more closely than all-time exporters in terms of size and other pertinent accounting and financial characteristics.

Given the relative unimportance of that extensive margin, the distinction between new exporters and purely domestic firms is also immaterial to the subsequent analysis. Attention will hence be devoted to purely domestic firms and continuing exporters in evaluating the impact of the Japan’s competitive devaluation.

**Cross-sectional Evidence**

As revealed by the summary statistics, companies that engage in export activity are distinct along a number of important dimensions. Table 1.2 tests whether multinationals are in fact systematically different from their counterparts based on more formal regression analysis for the period from 2010 to 2015. Columns (1)–(3) estimate OLS, Logit and Probit models on the subsample of public firms only; columns (4)–(6) do the same for the entire sample of firms. The discrete choice coefficient estimates present marginal effects at the means to facilitate comparisons with the OLS results.
Indeed, exporters are much larger than purely domestic firms in terms of their balance sheet size (log assets); they tend be more levered in the sample of all private and public firms; they differ in their cash-to-assets ratios; and are characterized by a higher price-to-book ratios, meaning that they are growth stocks in larger proportions than exclusively domestic companies. Looking at the subsample of public firms only, exporting firms also seem to exhibit higher levels of systemic risk by comoving more closely with the market, as reflected by a higher beta ($\beta$). Lastly, these stocks command lower abnormal returns ($\alpha$) than their purely domestic peers. Those differences suggest that all regressions should control for the main time-varying disparities among companies, such as size and other balance sheet items that have been widely used in the corporate finance literature and are pertinent to sales and employment choices.

[Insert Figures 3.5]

The results in Panel (a) of Figure 3.5 restrict attention to the subsample of public firms and plot the estimated $\psi_t$ coefficients of equation 1.1 for employment, domestic sales, and market capitalization as outcome variables with 95% confidence intervals around them. Panel (b) reports analogous results for the entire sample of public and private firms. As would be consistent with the parallel trends assumption, the estimates in Figure 3.5 show no robust differences between exporters and nonexporting firms in the years prior to the onset of Japan’s QQE policy: the estimated treatment effects capturing differences between both types of companies over time are indistinguishable from zero before the intervention, whereas they become negative and highly significant in the years following Abenomics. The results for public companies in Panel (a) show that exporters see their sales shrink by 15%, employment gradually decrease by about 6%, and market capitalization fall by about 10% relative to purely domestic firms.¹⁰

¹⁰In unreported figures, all of these outcome variables are shown to expand in levels and not just in relative terms between exporters and solely domestic firms. The steep reaction of stock prices to the yen devaluation is particularly surprising given the low overall levels of inflation observed during this period and the fact that exchange rates are often seen as “disconnected” from other variables.
Overall, and in sharp contrast to conventional open macroeconomic wisdom, exporters gain less from the nominal devaluation than exclusively domestic small caps and private firms. Importantly, the results are also robust to the inclusion of industry-year fixed effects, which further suggests that the adjustment patterns are driven by firm heterogeneity within rather than across industries—an observation that is built into the theoretical framework in section 1.4. A question arises regarding why Japan’s nominal devaluation had this puzzling differential impact on the dynamics of all-time exporters and purely domestic companies. After all, baseline macro models would predict that the former group should gain competitiveness in export markets as a result of the yen devaluation, yet the findings in Panels (a) and (b) of Figure 3.5 point toward the countervailing influence of rising marginal costs due to increasingly more expensive and poorly substitutable imported intermediate inputs. In fact, the findings are consistent with the marginal cost channel outweighing any positive effects in export markets and showing no signs of attenuating later on.

Mechanisms

To shed additional light on the role of intermediate inputs as the driving force behind the results, this section exploits disparities in the import content of production across industries by using the Japanese input-output tables in 2011. As it turns out, there is substantial heterogeneity across non-financial sectors in terms of their import reliance. As can be seen from the summary statistics in Table 1.1, the sectoral import content of production measure, $IC$, stands at around 6.3% for the lowest quartile of public firms, whereas it is 16.1% for the highest quartile. Assuming that exporters are also the biggest importers (as documented in Amiti et al. (2014)), one should, therefore, expect to see larger differences across purely domestic firms (nonimporters) and continuing exporters (importers) within industries that are more dependent on imported inputs. Essentially, this is tantamount to a triple difference methodology, where the above cross-sectional comparisons between nonexporters and ex-
porters are also made conditional on these firms operating in relatively import-reliant versus
-unreliant sectors.

[Insert Table 1.3 here]

Table 1.3 presents the estimation results for regression model 1.2 using the whole sam-
ple of public and private firms. The first two columns consider the treatment effect on
employment, and the last two columns use total domestic sales as the outcome variable.
Furthermore, regression results in columns (2) and (4) include all the main firm-level control
variables as well as their interaction terms with the Abenomics indicator in the specifica-
tions. This facilitates verification of whether any results can be attributed to a heterogeneous
reaction across firms of highly different natures to Japan’s large monetary stimulus rather
than the treatment allocation. Across all specifications, the estimated triple difference pa-
rameter, $\hat{\gamma}$, is negative and robustly statistically significant. The magnitudes imply that a
one-standard-deviation increase in the interaction term leads to employment gains at purely
domestic firms of 1.9% relative to exporters. Similarly, a one-standard-deviation rise in the
triple interaction term brings about domestic sales gains of 2.6% for nonexporters compared
to all-time exporters in sectors that are more dependent on imported intermediate inputs.
Firms operating in relatively import intensive industries positively affected in terms of their
home sales after the devaluation, as suggested by the positive coefficient estimates of $\beta_2$ in
columns (3)–(4). Finally, the lack of explanatory power in firms’ export treatment status
beyond its interaction term with sectoral import dependence, as reflected by the statistical
insignificance of the estimated $\beta_1$ coefficients, implies that all of the main results from before
were driven by the variation in firm import intensities across exporting and nonexporting
companies.

[Insert Figure 3.6 here]

Panel (a) of Figure 3.6 extends this analysis of the mechanism by using repeated ob-
servations for the same company over time and shows the estimated coefficient plots for
$\zeta_t$ in specification 1.3. As before, this methodology facilitates verification of the causal in-
terpretation of the results. Consistent with the parallel trends assumption, the estimates show no robust differences between nonexporting firms and exporters in the years prior to the introduction of Abenomics across industries sourcing intermediate inputs from abroad in varying degrees. After the policy, continuing exporters begin to shrink in terms of their sales and employment relative to domestic firms. The magnitudes of the results are similar to the ones in Table 1.3, still managing to yield statistically significant results at the 10% level for both home sales and employment by 2014. Given the lack of firm-level trade data, which would permit for a direct exploration of those channels, and given the noisy input-output measures for industrial intermediate input reliance, the strength and robustness of the findings are remarkable.

The analysis in this section has relied on the identifying assumption that exchange rate movements rather than any other factor exerted the primary differential influence on firms, and hence led to the trends observed following Japan’s large monetary stimulus. Another prominent hypothesis might highlight simultaneous interest rate shifts, yet the evidence is limited as far as downward pressure on the yield curve is concerned. Japanese long-term interest rates were already very low when Abenomics came into force, and they actually increased following the announcement of U.S. tapering in early 2013. This can be seen from Panel (b) in Figure 3.6, which shows the 8-year yield on JGBs, a security class that was heavily targeted during the Japanese QE interventions. Long-term interest rates only declined somewhat further toward 2015 and after the second round of quantitative easing, yet, by that time, all of the main cross-sectional effects had already set in: domestic sales, employment, and stock prices were rising for nonexporting firms relative to exporters. Besides, it would be hard to envisage a theory about why lower interest rates would generate the observed cross-sectional patterns between exporters and purely domestic firms. Interest

11 Very similar results can be obtained by defining a discrete measure of imported input reliance. Sectors belonging to the upper quintile of the import content of production distribution are then taken to be “import intensive”, and industries in the lower quintile are “unintensive”. By way of this approach, the gaps between nonexporters and exporters widen only in the import intensive industries.

12 The results are statistically significant at the 5% level for domestic sales starting from 2014 onward, and similarly for employment by 2015.
rate movements are hence very unlikely to have been the main explanatory factor behind the empirical results of this section. Lastly, potential confounding factors stemming from a revaluation of long-term debt are accounted for by the inclusion of leverage as well as its interaction term with the Abenomics indicator, allowing for a heterogeneous response to the stimulus across firms with varying degrees of exposure to long-term debt.$^{13}$

Taken together, these results inform a new theoretical paradigm that features a more realistic microstructure of the economy for thinking about the effects of monetary policy and competitive devaluations on firm dynamics. The model developed in section 1.4 thus embeds heterogeneous import intensities across firms as a key ingredient for successfully generating the observed cross-sectional patterns documented so far.

1.4 Model

This section develops a framework to help interpret the differential treatments effects between solely domestic firms and all-time exporters in section 1.3.3 and then uses it to understand the exact mechanism behind the dynamic adjustment path of the economy, allowing for a potential counter-factual analysis. The model links firm-level sales, employment and profit changes to exchange rates in an international setting and contrasts predictions of the classical Mundell–Fleming setup with the new paradigm.

The proposed static open economy consists of two countries of equal size, home (H) and foreign (F), which means that time subscripts can be avoided while the consumption and labor reallocation channels are elucidated in the most tractable fashion. As in the models of Obstfeld and Rogoff (2000), Obstfeld and Rogoff (1996), Hau (2000), and Blanchard and Kiyotaki (1987), firms produce differentiated goods using heterogeneous labor inputs indexed by $[0,1]$. One may think of each worker as occupying a point on the interval $[0,1]$ and acting as a monopolistic supplier of a distinctive variety of labor services. Workers are assumed

$^{13}$Yet another alternative story could stress a potential currency mismatch and differential exposure to dollar borrowing across firms. This phenomenon is extremely rare in Japan, with only a tiny fraction of companies ever having issued a Eurobond. See Bruno and Shin (2016) for more detail.
to set next period’s nominal wages in their domestic currency in advance of production and consumption. All labor is then supplied to firms in light of subsequently realized economic shocks, where the main focus will be on monetary shocks. Although wages are preset, domestic prices are completely flexible and can be changed in response to market conditions.

Home produces an array of differentiated tradable goods indexed by the interval [0,1], and foreign’s tradables are indexed by the interval [1,2]. In the most basic version of the model, tradable goods could be thought of as products of exporting firms, and one could assume that each country produces an array of differentiated nontraded goods indexed by [0,1], where the latter would be seen as output of purely domestic companies. But the framework will develop a more realistic version of the model based on the observation that all main patterns are observed within rather than across industries, making the distinction between tradable and nontradable sectors unimportant.

The model will incorporate several key ingredients from the international trade literature and apply them to the analysis of monetary policy in open economies. Firstly, and following Amiti et al. (2014), strategic complementarities and variable markups (as in Atkeson and Burstein (2008)) are combined with the Halpern et al. (2015) model of the firm’s choice to import intermediate inputs. That is, firms will be heterogeneous, choosing to sell products as well as to source intermediate inputs from abroad. The exchange rate will influence sales and employment via three potential channels: 1) by changing the costs of imported inputs, 2) by changing the export prices in local currency (depending on pricing assumption), and 3) by affecting the degree of import competition in the domestic market. While being less important qualitatively, incorporating strategic complementarities is crucial for improving the quantitative fit of the model.

Secondly, the following international pricing scenarios will be compared in turn: 1) producer currency pricing (PCP), 2) local currency pricing (LCP), and 3) dollar currency pricing (DCP). The last would be consistent with recent evidence suggesting that most trade around the world is invoiced in U.S. dollars (Gopinath (Forthcoming)) and is critical in reproducing
the patterns observed in section 1.3.3. The nominal exchange rate denoted $\epsilon$ is expressed as home currency per unit of foreign currency. Going forward, the home currency will often be referred to as yen and the foreign currency as dollar.

Motivated by the findings in Bilbiie et al. (2012) as well as by the empirical results in section 1.3.3 showing that entry into foreign sales is a negligible portion of the total volume, the export and import statuses of a firm are assumed to be fixed.\footnote{Besides, new firms account for a very small share of overall production and employment, meaning that it would also be safe to ignore the extensive margin for aggregate outcomes.} The trade literature (e.g., Halpern et al. (2015), or Amiti et al. (2014)) takes a thorough approach to separately modeling firm import and export decisions and finds that both are highly correlated in equilibrium as well as in the data. This implies that the majority of all firms are either exporters or nonexporter, and so the model will safely focus on these two types and thereby also mimic the main empirical discussion.

### 1.4.1 Households

A consumer of type $i$ maximizes utility derived from goods and minimizes disutility from labor. For simplicity of exposition separable constant-elasticity preferences over consumption and leisure are adopted. More precisely, the utility of a home representative household is given by:

$$
U_i = \log C_i - \frac{\kappa L_i^{1+\psi}}{1+\psi}
$$

(1.4)

where $L_i = \int [L_H(i, \omega) + L_N(i, \omega)] d\omega$ is the labor supply and $C_i$ is the consumption aggregator for any person $i$. The home consumption index depends on home and foreign tradables, and it can be written in the following form:

$$
C = \left[ \alpha^{1/\eta} C_H^{\eta-1} + (1 - \alpha)^{1/\eta} C_F^{\eta-1} \right]^{\eta/(\eta-1)}
$$

(1.5)
where $C_H$ is the home consumption of domestic tradable goods, and $C_F$ is home consumption of foreign tradables. The foreign country has a parallel indexes, but with a weight of $\alpha^* > 1/2$ on consumption of its own export good. These assumptions generate home bias in consumption within the category of tradable goods and can be thought of as a substitute of explicit trade costs for tradable goods.

The $\eta$ parameter is the constant elasticity of substitution between domestically produced and imported tradables, and it underlies the magnitude of price responses to quantity adjustments. A lower substitution elasticity implies that sharper prices changes are required to accommodate a given adjustment to quantities consumed.

The domestic consumer price index (CPI) corresponding to the consumption index $C$, measured in units of domestic currency, depends on the local prices of home and foreign produced tradables, $P_H$ and $P_F$, according to the formula:

$$P = \left[ \alpha P_H^{1-\eta} + (1-\alpha) P_F^{1-\eta} \right]^{\frac{1}{1-\eta}} \quad (1.6)$$

In the foreign country, there is an isomorphic index of tradable prices and nominal CPI with weight $\alpha^*$ attached to foreign exportable goods. The home demand functions resulting from utility maximization are:

$$C_H = \alpha \left( \frac{P_H}{P_T} \right)^{-\eta} C, \quad C_F = (1-\alpha) \left( \frac{P_F}{P_T} \right)^{-\eta} C \quad (1.7)$$

**Differentiated Goods**

Consumers in each market are assumed to have a nested CES demand over varieties of goods. In other words, the tradable sector consists of domestic and foreign goods, where both $C_H$ and $C_F$ are indexes of the consumption of domestic and foreign goods given by the constant
elasticity of substitution functions:

\[ C_H = \left( \int_0^1 C_H(\omega)^{\frac{\rho-1}{\rho}} \, d\omega \right)^{\frac{\rho}{\rho-1}}, \quad C_F = \left( \int_0^1 C_F(\omega)^{\frac{\rho-1}{\rho}} \, d\omega \right)^{\frac{\rho}{\rho-1}} \] (1.8)

where \( \omega \in [0, 1] \) denotes the good variety, and each country produces a continuum of differentiated goods on the unit interval. The elasticity of substitution across the varieties within a sector is \( \rho \), while the elasticity of substitution between domestic and foreign goods is \( \eta \). Varieties within an index are assumed to be more substitutable than the home and foreign goods: \( \rho > \eta \geq 1 \).

Consumers maximize utility, given by equation 1.4 subject to their budget and cash-in-advance constraints. A firm producing a differentiated good \( \omega \) and supplying it to destination market \( k \in \{H, F\} \) will face a demand function given by:

\[ C_k(\omega) = \left( \frac{P_k(\omega)}{P_k} \right)^{-\rho} C_k \] (1.9)

where, for \( k \in \{H, F\} \), \( P_k = \left( \int_0^1 P_k(\omega)^{1-\rho} \, d\omega \right)^{1/(1-\rho)} \) is either the index of prices of domestically or foreign produced goods. Combining the above optimality conditions in equation 1.9 with the definitions of the price and quantity indexes, \( P_k \) and \( C_k \), yields \( \int_0^1 P_k(\omega)C_k(\omega) \, d\omega = P_kC_k \). Lastly, the optimal allocation of expenditures between domestic (H) and imported (F) goods is given by:

\[ C_H = \alpha \left( \frac{P_H}{P} \right)^{-\eta} C, \quad C_F = (1 - \alpha) \left( \frac{P_F}{P} \right)^{-\eta} C \] (1.10)

where \( P = [\alpha P_H^{1-\eta} + (1 - \alpha) P_F^{1-\eta}]^{1/(1-\eta)} \) is the CPI, and total consumption expenditures by domestic households are \( P_H C_H + P_F C_F = PC \).
1.4.2 Firms

There are two types of firms operating in the tradable sectors of both the home and foreign economies: purely domestic (D) and exporters (E).\footnote{As in much of the trade literature (e.g., Melitz\citeyear{2003}), the former can be thought of as less productive companies that are unable to recoup the fixed costs of exporting, and the latter as more productive companies, catering to both domestic and foreign markets.} In general, firms in the tradable sector use labor, $L(\omega)$, and imported intermediate inputs, $X(\omega)$, to produce a unique variety $\omega$. The production function is:

$$Y_H(\omega) = A_\omega L(\omega)^{1-\phi} X(\omega)^{\phi}$$  \hspace{1cm} (1.11)

where $A_\omega$ captures firm productivity, $X(\omega)$ is a bundle of diverse intermediate inputs produced abroad, and the labor input, $L(\omega)$, is a CES aggregator of the individual labor varieties supplied by each household:

$$L(\omega) = \left[ \int L(i, \omega) \frac{\phi - 1}{\phi} \, di \right]^{\frac{1}{\phi - 1}}, \quad \phi > 1$$  \hspace{1cm} (1.12)

Here, $L(i, \omega)$ is the demand for labor input $i$ by producer $\omega$. Letting $W_i$ stand for the nominal wage of worker $i$, the price index for labor inputs, $W$, is given by:

$$W = \left[ \int W_i^{1 - \phi} \, di \right]^{\frac{1}{1 - \phi}}$$  \hspace{1cm} (1.13)

There are parallel production functions with the same substitution elasticity, $\phi$, for foreign-produced tradables, $Y_F(i)$. Splitting output between the home and foreign markets, $Y = Y_H + Y^*_H$, the firm’s per-period profits (distributed to domestic households) are given by:

$$\Pi(\omega) = \Pi_H(\omega) + \Pi^*_H(\omega)$$

$$= (P_H(\omega) - MC(\omega)) Y_H(\omega) + (P^*_H(\omega) - MC(\omega)) Y^*_H(\omega)$$  \hspace{1cm} (1.14)
Marginal costs are then:

$$MC(\omega) = \frac{W^{1-\varphi_\omega} P_X^{\varphi_\omega}(\omega)}{\tilde{A}_\omega}$$

(1.15)

where $W$ is taken as given (from equation 1.13) and does not vary across firms, while the imported inputs price index is equal to: $P_X(\omega) = \epsilon P^*_X(\omega)$ and varies across firms to the extent that they import different measures of intermediate input varieties.

Holding everything else constant, the larger the measure of imported varieties used, the lower the intermediate input cost index. Also, $P^*_X$ is the cost index of imported intermediate inputs in foreign currency, $\epsilon$ is the nominal exchange rate, $\varphi_\omega$ is the firm’s import intensity, and $\tilde{A}_\omega$ is the company’s productivity term.

A microfoundation for this type of cost structure, where the import intensity, $\varphi_\omega$, and the set of imported intermediate inputs are endogenously determined by firms with fixed costs of importing, $F$, in ways that are consistent with the data is provided in the trade literature (Amiti et al. (2016), Halpern et al. (2015)). Since import intensities are not directly observable, the parameter $\varphi_\omega$ will take two values in this paper, as discussed in section 1.5. The optimality conditions for hiring labor are given by:

$$L(\omega) = \frac{(1-\varphi_\omega)MC(\omega)Y(\omega)}{W}, \quad L(i,\omega) = \left[\frac{W_i}{W}\right]^{-\varphi}L(\omega)$$

(1.16)

And the optimality condition for intermediate inputs is:

$$X(\omega) = \frac{\varphi_\omega MC(\omega)Y(\omega)}{P_X}$$

(1.17)

### 1.4.3 Asset markets and budget constraints

There are complete markets, so agents can trade state-contingent securities in complete set of financial markets before the realization of the state of the world $s \in S$, with density $\pi(s)$. All agents own an equal share of domestic firms and of an initial stock of the domestic
currency. There is no ex-ante trade in equity between countries. Money is introduced into the model by means of a cash-in-advance constraint:

\[ P(s)C_i(s) \leq M_i(s) \]  

(1.18)

while a typical individual \( i \) in the home country maximizes the expectation of equation 1.4 subject to the following two budget constraints:

\[ \int D_i(s)Q(s)\pi(s)\,ds = 0 \]  

(1.19)

\[ P(s)C_i(s) + M_i(s) \leq W_iL_i(s) + \int [\Pi_H(j, s) + \Pi_N(j, s)]\,dj + T_i(s) + D_i(s) \]  

(1.20)

where \( Q(s) \) is the price of one unit of domestic currency in state \( s \), normalized by the probability of state \( s \), \( W_iL_i(s) \) is labor income, where the wage is preset and does not depend on \( s \), \( T_i(s) \) is a lump-sum transfer, \( D_i(s) \) are state-contingent net foreign assets denoted in home currency held by the domestic household \( i \), and the integral in the second constraint aggregates profits of all domestic firms. Individuals take firm behavior as given. The home government budget constraint is given by:

\[ M = T \]  

(1.21)

So the government is assumed to rebate all lump-sum transfers in the form of money.\(^{16}\)

\(^{16}\)It is also assumed that the government buys back the whole outstanding money supply at the end of the period, financing the operation with lump sum taxes imposed on the consumption good. By doing that, the government effectively has the freedom to choose the price level and thereby ensures a monetary equilibrium. In particular, because the government is choosing how many consumption goods will pay for \( M \), it can set \( M/p \) and implement \( M/p > 0 \).
1.4.4 Wage Setting

Using the individual’s budget constraint (equation 1.20) to eliminate $C_i$ in the utility function, the first order condition for the optimal preset nominal wage, $W_i$, is:

$$W_i = \left( \frac{\phi}{1-\phi} \right) \frac{E[kL_i^{\psi+1}]}{E[L_i/PC_i]}$$  \hspace{1cm} (1.22)

Here, the expectation operator in equation 1.22 reflects the monetary uncertainty faced by households. At an optimum, this wage-setting formula requires the expected marginal revenue (in marginal utility of consumption) from raising the wage a little bit to be equal to the expected marginal utility from the fewer hours worked as a result. Without monetary or exchange rate uncertainty, the relationship would simply give the marginal utility of the real wage as a fixed markup over the marginal disutility of labor, as is standard for a monopolist facing a constant elasticity of demand.

1.4.5 Price Setting

This section assumes constant markups and the use of domestic currency for pricing at home. Monopolistically competitive firms may set their domestic prices at whatever levels they choose. However, since individuals have constant elasticity of demand preferences, revenue maximizing firms in the single sector economy will choose prices for goods that are a constant markup over their marginal costs.

Outcomes under three alternative pricing assumptions in international markets are contrasted: producer currency pricing (PCP), local currency pricing (LCP), and dollar currency pricing (DCP). Throughout, firms choose prices domestically and abroad to maximize their profits, $\Pi(\omega) = \Pi_H(\omega) + \Pi_{H}^*(\omega)$. 

34
Dollar Currency Pricing

When home prices are set in domestic currency and international prices are set in dollars, profit maximization at home (w.r.t. \( P_H(\omega) \)) and abroad (w.r.t. \( P^*_H(\omega) \)) implies:

\[
\mathcal{P}_H(\omega) = \left( \frac{\rho}{\rho - 1} \right) MC(\omega), \quad \mathcal{P}^*_H(\omega) = \frac{1}{\epsilon} \left( \frac{\rho}{\rho - 1} \right) MC(\omega) \quad (1.23)
\]

As usual, when firms compete in prices, they set a multiplicative markup \( \rho/(\rho - 1) \) over their costs. Any ex-post fluctuations in the nominal exchange rate, \( \epsilon \), will affect repatriated profits, \( \Pi^*_H(\omega) \), but will not influence the pre-set dollar price. Meanwhile, imported intermediate input prices are also set in dollars, \( P^*_X \), and the price of imported consumption goods is given by:

\[
P_F = \epsilon \mathcal{P}^*_F = \epsilon \left( \frac{\rho}{\rho - 1} \right) MC(\omega)^* \quad (1.24)
\]

Under this form of price stickiness, nominal exchange rate changes lead to proportional short-run deviations from the law of one price. With import prices preset in the importer’s rather than the exporter’s currency, the short-run degree of exchange rate pass-through to import prices is exactly zero.

Producer Currency Pricing

When home and international prices are set in producer currency, profit maximization at home and abroad (w.r.t. \( P_H(\omega) \)) implies the same relationships as in (1.23), but nominal exchange rate movements will now lead to fluctuations in the foreign currency prices of exports. Accordingly:

\[
\mathcal{P}_H(\omega) = \left( \frac{\rho}{\rho - 1} \right) MC(\omega), \quad P^*_H(\omega) = \frac{1}{\epsilon} \mathcal{P}_H = \frac{1}{\epsilon} \left( \frac{\rho}{\rho - 1} \right) MC(\omega) \quad (1.25)
\]

Similarly, imports will be priced in producer currency, as in equation (1.24).
Local Currency Pricing

Now consider the alternative case of local currency pricing. The mechanism of a nominal exchange rate devaluation under LCP is somewhat different from before. Under PCP, a currency depreciation affects international relative consumer prices, whereas under LCP, profit margins are affected while prices stay unchanged.

The local currency pricing case is almost identical to dollar currency pricing, except that import prices are now also set in local currency rather than dollars. Hence equations (1.23) will still hold for the home good, intermediate input prices will not be sensitive to exchange rate fluctuations but fixed at $P_X$, and imported goods prices will be pre-determined in the home currency:

$$P_F = \epsilon P^* = \epsilon \left( \frac{\rho}{\rho - 1} \right) MC(\omega)^*$$

(1.26)

Strategic Complementarities

The above price setting assumptions can be tweaked to allow for variable markups and strategic complementarities. This will be particularly important in producing a better quantitative fit of the model in section 1.5. As in Itskohki and Mukhin (2016), price setting of domestic firms is assumed to take the following form under DCP:

$$P_H(\omega) = \frac{\rho}{\rho - 1} (MC(\omega))^{1-\zeta} \cdot P^\zeta$$

(1.27)

$$P_H^*(\omega) = \frac{\rho}{\rho - 1} (MC(\omega)/\epsilon)^{1-\zeta} \cdot (P^*)^\zeta$$

(1.28)

Here, $\zeta \in [0, 1)$ is the strategic complementarity elasticity. Equations (1.27) are ad hoc but can be made consistent with a large range of price setting models, such as both monopolistic and oligopolistic competition models under CES and non-CES demand.

Strategic complementarities in price setting, when $\zeta > 0$, reflect the tendency of companies to set prices closer to their local competitors, a pattern which is both pronounced in the
data and emerges in a variety of models (as in Amiti et al. (2016)). Since these price setting assumptions are consistent with a version of Kimball (1995) demand, they are referred to as such in the quantitative section.

1.4.6 Market Clearing

The home market for tradable goods clears when domestic demand equals domestic supply (the foreign country faces a parallel condition):

\[ Y_H = C_H + C_H^* = \alpha \left( \frac{P_H}{P} \right)^{-\eta} C + (1 - \alpha^*) \left( \frac{P_H/\epsilon}{P^*} \right)^{-\eta} C^* \]  

(1.29)

Domestic net exports measured in home currency are defined as:

\[ NX = \epsilon P^* C_H^* - P_F C_F \]  

(1.30)

1.4.7 Competitive Devaluations

Having fully described the static complete markets DCP, PCP or LCP economy, the last remaining block needs to specify nominal exchange rate determination. The utility function in equation 1.4 together with the cash-in-advance (CIA) constraint and complete markets imply the following simple relationship\(^{17}\)

\[ \epsilon = \frac{M}{M^*} \]  

(1.31)

1.4.8 Equilibrium

Solving for the competitive equilibrium of the DCP, PCP and LCP models entails the following conditions to hold:

\(^{17}\)The same condition is derived in Kehoe and Midrigan (2007).
1) Household optimization, firm optimization, and either DCP (equations [1.23] and [1.24]), or PCP (equations [1.25]), or LCP (equations [1.23] and [1.26]).

2) Markets clear such that: \( Y_H = C_H + C_H^* \), and \( Y_F^* = C_F + C_F^* \).

3) The monetary block is described by equation [1.31], and money demand is given by the cash-in-advance constraint in equation [1.18].

This completes the description of the modeling environment. The next sections present analytical results for intuition and turn to a numerical analysis that contrasts outcomes following a competitive devaluation under the three pricing regimes.

1.4.9 Comparative Statics

In order to build some intuition for how the relative allocations between productive exporters and unproductive nonexporters shift in the aftermath of a competitive devaluation, consider the consumption ratio of two distinct firms. The objective is to compare what happens to the ratio of \( C_H(\omega) \) to \( C_H(\tilde{\omega}) \), where the initial firm is an exporter and the latter is not, i.e. with \( \varphi_\omega > \varphi_{\tilde{\omega}} \), following a nominal devaluation under the dollar currency pricing (DCP) regime. Define:

\[
\Delta C \equiv \ln \left( \frac{C_H(\omega)}{C_H(\tilde{\omega})} \right) = \rho \left( \ln P_H(\tilde{\omega}) - \ln P_H(\omega) \right) = \rho \left( \ln MC(\tilde{\omega}) - \ln MC(\omega) \right)
\]

And now consider how \( \Delta C \) changes with the nominal exchange rate:

\[
\frac{\partial \Delta C}{\partial \ln \epsilon} = \rho \left( \varphi_{\tilde{\omega}} \frac{\partial \ln P_X(\tilde{\omega})}{\partial \ln \epsilon} - \varphi_\omega \frac{\partial \ln P_X(\omega)}{\partial \ln \epsilon} \right) = \rho \left( \varphi_{\tilde{\omega}} - \varphi_\omega \right) < 0 \quad \text{since: } \varphi_\omega > \varphi_{\tilde{\omega}}
\]
As long as higher productivity firms have a larger import intensity than lower productivity firms do, the elasticity of \( C_H(\omega)/C_H(\tilde{\omega}) \) with respect to the nominal exchange rate is negative. This means that a competitive devaluation should lead to a relative expansion of less productive domestic firms at home.

A similar relationship holds for relative employment across the two types of firms. The only difference is the presence of slightly offsetting effects due to the increasing marginal cost side and the decreasing amount of output that results from the fall in demand following higher prices. The analogous expressions becomes:

\[
\Delta L \equiv \ln \left( \frac{L_H(\omega)}{L_H(\tilde{\omega})} \right)
\]

\[
\frac{\partial \Delta L}{\partial \ln \epsilon} = (\rho - 1)(\varphi_{\tilde{\omega}} - \varphi_{\omega}) < 0
\]

Overall, employment shrinks at the more productive firms relative to the less productive nonexporters, albeit at a smaller rate than the ratios of consumption.

The predictions of the baseline model for relative consumption and employment growth as well as for the response of prices and net exports are then inconsistent with the data. At the same time, those moments characterize the dynamic adjustment path of an economy, and conventional wisdom often stresses the importance of nurturing national export champions that can spur economic growth following efforts to weaken the currency. Any coherent theory of competitive devaluations should, therefore, be expected to match those moments more successfully.

### 1.5 Quantitative Results

This section numerically evaluates the impact of competitive devaluations on firms’ relative profitability, consumption, and employment allocations. Nominal exchange rate devaluations of diverse intensity are considered and outcomes are judged against a pre-shock equilibrium
for the three price setting scenarios and for varying degrees of intermediate import intensity. The two country economy framework developed in section 1.4 is used for delving into the mechanisms by which international shocks are transmitted into domestic prices and quantities in light of the firm-level empirical findings of section 3.3. To that end, a tightly calibrated quantitative model that captures the cross-sectional heterogeneity observed in Japan’s manufacturing industries is employed to show how the interaction of dollar currency pricing and import intensities shapes aggregate and firm-level reactions following a competitive devaluation as observed during Abenomics.

1.5.1 Parameter Values

Consider a representative industry with domestic nonexporting (D) as well as exporting (E) firms in both countries. The representative sector will be calibrated to one that is typical in the Japanese data, focusing on the domestic market in which both domestic and foreign (say, US) firms compete. In a given Japanese industry, three types of firms are operating: $N_E$ home exporters (serving both domestic consumers and the foreign market), $N_D$ solely domestic firms, and $N_F$ foreign firms. To approximate one of the features of the Japanese domestic market, the number of firms is calibrated to match an average SIC industry. In particular, the industry is taken to be composed of 300 firms ($N$) in both countries, and firms in each economy are born with an idiosyncratic marginal cost draw from the distribution $G(A)$. The entry decision into the domestic market happens automatically and is not modeled for simplicity. Meanwhile, the total number of firms headquartered at home and abroad that sell positive amounts of their goods in each country (exporters) is determined endogenously in equilibrium. In other words, firms will simultaneously choose to export and import intermediate inputs if such a decision yields additional profit for them.

The fraction of Japanese (and US) manufacturing firms that export and import is set to be the 10% most productive companies of the total number of firms in the industry. That
said, the key outcomes of the model are insensitive to specifying a smaller competitive fringe with a larger percentage of firms participating in international trade.\footnote{Bernard and Jensen (2004) report the fraction of exporters in total plants to be 21\% in 1987 and 30\% in 1992. The baseline calibration in this paper will specify a larger competitive fringe, with many small firms capturing minuscule portions of the overall industry production volume.}

The marginal cost of a firm is modeled just like in section \ref{sec:marginal_cost}, more precisely:

\[
MC(\omega) = \frac{W^{1-\varphi_\omega}[\epsilon P_X^*(\omega)]^{\varphi_\omega}}{A_\omega}
\]  

(1.32)

where $W$ is the price of labor (or domestic inputs), $P_X^*(\omega)$ is the foreign-currency price index of foreign (imported) inputs, $\epsilon$ is the nominal exchange rate, and $A_\omega$ is the effective idiosyncratic productivity of the firm. In general, imported intermediate input prices do not have to depend on $\omega$, because the formulation would still capture the idiosyncratic heterogeneity in input prices from before through the effective idiosyncratic productivity term $A_\omega$. As in the recent trade literature, the exchange rate exposure term, $\varphi_\omega$, is assumed to be firm-specific and constant over time. Amiti et al. (2014) show this assumption to be justified using Belgian trade data, with firm-level import intensities not being sensitive to exchange rate movements over a horizon over 3–5 years. Using that formulation, $P_X^*(\omega)$ will be lower for exporters (that are also importers) than for nonexporters, and the price of intermediates is assumed not to move with the exchange rate, which is consistent with pass-through into import prices being slow and incomplete. Following Halpern et al. (2015), the cost-savings from importing are calibrated to be equal to 20\% of production costs, meaning that firms compare the fixed costs of becoming exporters with the added benefits from lower marginal costs.

[Insert Table 1.5 here]
as well as for simplicity and consistency with the nominal wage rigidity assumption of the model, the following normalizations are imposed: \( W = 1, [P_X^*]^D = 1 \) for nonexporters, which means \([P_X^*]^E = 0.8\) for exporters. Initial firm productivities are drawn from a log-normal distribution, \( A^{-1} \sim \ln N(\mu_A, \sigma_A^2) \), where \( \mu_A \) is the location, and \( \sigma_A \) the scale parameters of the distribution. In the calibration, \( \sigma_A = 0.1, \mu_A = 1 \). Exporting firms draw their costs from the same distribution but end up being the most productive 10%. Given the other parameters of the model (including the demand elasticity \( \rho \)), this allows one to match the cross-sectional differences in profits, sales and employment patterns following a nominal devaluation.

The home bias parameter, \( \alpha \), is set to 0.93 in both countries, reflecting the fact that both Japan and the U.S. are relatively closed economies. Exports as well as imports are separately equal to about 14% of GDP for both Japan and the US, and given that final consumption is about half of total imports, with the rest capturing intermediate inputs, this ends up producing a 7% foreign share parameter. The exchange rate exposure across firms, \( \varphi(\omega) \), is calibrated to reproduce the sales allocations across different types of companies in the data. For domestic nonexporting firms, \( \varphi(\omega)^D = 0 \), whereas for all-time exporters, this import intensity measure is set to \( \varphi(\omega)^E = 0.4 \). Because the information on import intensities is not directly observable in the data, this calibration enables the differential home sales and employment trends to be matched across both groups of companies. In addition, these parameter values help replicating the muted net exports reaction. As shown in Amiti et al. (2014), exporters are more import intensive than exclusively domestic firms are, and that feature is captured in the calibration. As mentioned, import intensities are also assumed to remain fixed independent of exchange fluctuations, which is a good approximation over horizons of 3–5 years.

Having specified the distribution of costs (or productivities) for both types of firms, \( \{MC(\omega)\} \), equilibrium prices are firstly calculated assuming constant markups and CES demand—that is, according to equations 1.23, which then allows one to solve for industry...
and aggregate prices as well as the remaining allocations. \cite{AndersonVanWincoop2004} survey the evidence on the elasticity of demand for imports at the sectoral level and conclude that this elasticity is likely to be in the range of 5 to 10. Even though the results in this paper are robust to a wide range of parameter choices, the elasticity of substitution across home and foreign goods is set to $\eta = 2$, and the elasticity of substitution between varieties within home or foreign goods is chosen to be $\rho = 6$, a value near the middle of a relatively wide range of estimates found in much of the literature. To better match the quantitative predictions of the model, the second approach to solve for prices is via a Kimball demand specification, as in equation 1.27. The parameter $\zeta$ is set to 0.7, which is somewhat larger than estimated by \cite{Amiti2016} but still in line with much of the markup and pass-through literature, especially given the low price reactions to exchange rates documented in Japan.

1.5.2 Model Fit

Before turning to counterfactuals and policy implications, the calibrated model is verified to reproduce the key empirical mechanism of section 1.3.3. This is shown by rerunning specification 1.2 on data simulated from the model, where the results are reported in Table 1.4. In parallel to the empirical mechanism in Table 1.3, a firm’s employment and domestic sales (in columns (1) and (2)) are regressed on a set of firm fixed effects, the $QE_t$ dummy, as well as the following interaction terms: $(Treat_i \cdot QE_t)$, $(IC_j \cdot QE_t)$, and $(Treat_i \cdot IC_j \cdot QE_t)$. As before, $Treat_i$ is an indicator variable equal to 1 whenever a firm is an exporter and 0 when the firm is entirely domestic, and $IC_j$ equals 1 when exporters in the industry have an import intensity of 40% (i.e., $\phi_\omega = 0.4$), whereas $IC_j$ takes on the value of 0 if exporters, just like purely domestic firms, do not source any intermediate inputs from abroad (i.e., $\phi_\omega = 0$). In addition, the natural logarithm of model generated prices is now also included as one of the outcome variables in column (3) of Table 1.4. The estimated coefficients show that, following a 30% nominal devaluation, the model nails the analog of $\gamma$ in specification 1.2 of section
3.3 In other words, the model predicts that exporters will shrink relative to nonexporters only in import reliant sectors, as observed in real world data. Indeed, the results in column (3) of Table 1.4 suggest that exporters in such industries will be forced to increase prices more than their nonexporting peers, which leads them to lose market share as a result.

[Insert Table 1.4 here]

This analysis confirms that the calibrated model delivers on salient features of firm behavior in the data, and can be used for counterfactual analysis. Primarily, though, the framework is utilized to help interpret the main empirical patterns of quantity adjustment and price setting by Japanese companies following Abenomics. Using the calibrated model, simulations of the industry are run for various levels of domestic monetary stimuli and for nominal devaluations reaching 50% relative the pre-shock equilibrium. Given the calibrated exogenous marginal cost process in equation 1.32, the model is used to solve for firm- and sector-level prices and allocations. Comparing domestic nonexporters with all-time exporters in Japan, the focus is on the response of domestic prices, total profits, home sales, and employment. Furthermore, aggregate domestic output, the price index, and the evolution of net exports are studied following the interventions. To understand the mechanisms behind the empirical findings, successively more realistic versions of the model are compared.

[Insert Table 1.6 here]

Ultimately, the model reveals that the seemingly puzzling cross-sectional phenomena can be rationalized in a framework with three key ingredients: firm heterogeneity, heterogeneous import intensities and dollar currency pricing. The addition of strategic complementarities in price setting is useful for improving the quantitative fit but unimportant for the main qualitative predictions. Because all of the main empirical patterns hold within rather than across industries, the discussion going forward will limit itself to the case of a one-sector economy, dispensing with nontradable goods all together as in the main model developed in section 1.4. All key empirical moments are summarized in Table 1.6 together with a comparison of the benchmark model’s performance along with more rudimentary versions.
of the framework, adding the necessary ingredients step-by-step. The mechanisms by which each additional feature improves the qualitative and quantitative predictions of the model are discussed next.

**Mundell–Fleming Environment**

To study the implications of competitive devaluations in a one-sector version of the model that would correspond to the classic Obstfeld–Rogoff (or Mundell–Fleming) framework, the following parameter values are also imposed: firstly, the dispersion of firms’ productivity draws is set to equal zero, $\sigma_A = 0^{19}$. This effectively shuts down any type of firm heterogeneity and disables all barriers to trade, meaning that all firms choose participate in exporting. Secondly, the price setting assumptions conform to the standard PCP constant markup version of the model presented in section 1.4.5.

[Insert Figure 1.6 here]

Figure 1.6 plots the economy’s response to monetary infusions (and hence competitive devaluations) of varying strength. Throughout the exercise, foreign money supply is normalized at unity, and domestic money supply is perturbed upwards. The magnitudes of the nominal devaluation are chosen to mimic the ones observed in Japan from late 2012 until 2015, although the baseline comparison will be to look at a 30% devaluation and compare it with the empirical patterns seen in Japan around 2014. As expected from the theory, both the firm-level reactions in Panel (a) as well as the macroeconomic response in Panel (b) fail to even remotely match the data. Because all firms are homogeneous, do not source intermediate inputs from abroad, and set prices according to a constant markup over marginal costs, companies are not induced to adjust on any margin following the devaluation. Meanwhile, profits, sales and employment shoot up almost linearly along with the nominal depreciation as products supplied by import competition become relatively more expensive and consumers

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19 If there were fixed costs of exporting (as well as importing), these would also be set to zero.
substitute toward domestically produced goods. Also, firms benefit from expenditure switching in the foreign market as their goods become relatively more competitive abroad.

The performance of the standard PCP framework in predicting aggregate adjustments is just as poor. The price index is almost completely unresponsive and rises only by about 1% as a result of imported inflation. Net exports to pre-shock GDP increases by about 4–5% following a 30% nominal devaluation, as would be consistent with standard intuition and the expenditure switching mechanism. A more fundamental deficiency of the present framework, which will not be fully resolved throughout the model, is that any New Keynesian setup with nominal rigidities produces a large domestic stimulus, which is counterfactual in the case of Japan, where real GDP growth was slow and barely positive around 2014. A likely reason for such an extremely weak reaction of GDP could be the rising consumption tax (from 5% to 8%), the expectation and announcement of further consumption tax hikes, and the overall contractionary fiscal policy environment referred to in the empirical section.

Table 1.6 summarizes the key numerical predictions of the Mundell–Fleming model in the MF column. Taken together, this basic setup fails to reproduce the empirically observed dynamic adjustment path of the economy along every dimension and consequently yields an erroneous prediction for key outcome variables that any coherent theory of competitive devaluations should match with greater success. Modifying this framework along the well-known local currency pricing (LCP) paradigm does not provide a satisfactory solution despite managing to shut down the expenditure switching channel and thereby muting the trade balance reaction. As can be gauged from the results in the first M1 column of Table 1.6, none of the firm-level micro adjustment patterns are reproduced by simply modifying that price setting assumption.

\[ \text{It should be noted, however, that manufacturing output did react a lot more strongly to the nominal devaluation, rising by about 10% from early 2013 to mid 2014. It is possible, therefore, to imagine a setup where the industrial sector is subject to a binding cash-in-advance constraint while the remaining industries operate in a credit economy and remain insensitive to the monetary expansion.} \]
Dollar Currency Pricing with Heterogeneous Firms

In order to make progress in matching the firm-level transmission channels, a number of ingredients from the international trade and macro literatures are introduced. By construction, firm heterogeneity is the first essential component to talk meaningfully about differential effects on various types of companies. This means that the dispersion of productivity draws will be set to positive levels and the top 10% most productive companies will be simultaneously exporting and importing, as discussed in section 1.5.1. All of the key parameter values used in the present version of the model are summarized in Table 1.5. Firm heterogeneity is far from being enough, though, because some other force is required to constrain exporters in their domestic expansion following nominal devaluations. Consistent with the empirical results of section 3.3, heterogeneous import intensities for intermediate inputs and dollar currency pricing turn out to be the two missing components. Notably, heterogeneous import intensities together with local (rather than dollar) currency pricing are not enough because in that case, nominal exchange rate movements still would not influence firms’ marginal costs (see the M2 version of the model in Table 1.6). It is only with dollar currency pricing that firms are negatively affected if they import (and export) and also fail to reap the benefits from a relative reduction in their export price levels abroad.

[Insert Figure 1.7 here]

Figure 1.7 shows how the economy reacts to monetary infusions of varying strength at both micro- and macro-levels. Now, simulation results for both types of firms, solely domestic (in circles) and exporters (in squares), are shown in Panel (a). Due to their higher reliance on imported intermediate inputs and international dollar invoicing, all-time exporters are now forced to increase their domestic prices a lot more than domestic nonexporters are. These movements in turn translate into lower profits and expenditure switching toward varieties produced by purely domestic companies. As a result, domestic sales and employment follow vastly different expansion paths for these two types of firms after the interventions. Even though the general micro patterns now point in the right direction, as shown in the M3
column of Table 1.6, the relative expansion of nonexporters is now much higher than observed in the data.

[Insert Figure 1.8 here]

However, the quantitative fit of the model is much improved with the addition of a fourth ingredient: strategic complementarities in price setting (see Amiti et al. (2016)), as described in section 1.4.5. Interestingly, with this form of variable markups, both exporters and nonexporters now optimally choose to increase their prices following the competitive devaluation, as can be discerned from Figure 1.8. The Benchmark column of Table 1.6 shows that this version of the model is vastly more successful in matching the relative percentage increase in the sales ratio gap between solely domestic and exporting firms, and similarly for the remaining firm-level moments. The aggregate patterns continue to suffer from a larger than observed output reaction, yet manage to display inflation and trade balance patterns that are much closer to the ones observed in the Japan following Abenomics.

1.5.3 Counterfactuals and Policy Implications

Alternative Price Setting

Consider first an economy with the identical level of firm heterogeneity and the same intermediate import intensities as in the benchmark model, but with a different price setting regime. In particular, take a world of exclusively producer currency pricing (PCP). This can be thought of as a counterfactual scenario in which the U.S. dollar does not have its special role, or a case in which the use of producer currency for international transactions is promoted by regulation.\footnote{Certain emerging economies have resorted to policies that target firms currency choices in the past. Even though trade was exempt, Indonesia made its currency mandatory for most transactions as of July 1, 2015. Another example is the Bank of Korea’s providing importers with loans in South Korean won through local banks in order to promote local currency invoicing and settlement.}

Compared with the case of international dollar currency pricing, Japanese exporters would now gain competitiveness abroad, as in the standard Mundell–Fleming paradigm,
yet they would still be hurt by rising imported intermediate input costs. Meanwhile, the U.S. economy will be less insulated than under DCP, with expenditure switching toward increasingly cheaper Japanese final goods and with rising imported input costs (now invoiced in yen) forcing U.S. firms to increase prices more. A counterfactual simulation reveals that Japan’s trade balance is virtually unaffected by a 30% yen devaluation. Also, due to the gains in competitiveness experienced by Japanese exporters abroad, the gap between labor and profit growth for nonexporters relative to exports is now only 5%. These counter-factual scenarios point to the fact that the U.S. benefits from the international role of the dollar not just through its own monetary policy spillovers but also as a result of greater insulation from nominal devaluations undertaken abroad.

**Alternative Import Intensities**

The second counterfactual world considered in this discussion keeps the dollar currency pricing paradigm intact but assumes an alternative dispersion of firm import intensities. This scenario is useful for evaluating the channels of monetary policy transmission in open economies with varying dependencies on intermediate imported inputs.\(^{22}\)

A simulation that sets the import intensity of exporters, \(\varphi_\omega\), equal to 0.7 and leaves all other parameters unchanged reveals that CPI inflation would rise by 6% and the trade balance to pre-shock GDP ratio would fall by 3.5%. The prior differences between domestic nonexporters and multinationals would naturally increase as well. Those results provide a word of caution against the use of unconventional monetary policy or competitive devaluations in countries with high degrees of vertical specialization forming a part of global value chains. By contrast, setting \(\varphi_\omega = 0.1\) shrinks the gap between the expansion paths of nonexporters and exporters and, more importantly, yields aggregate inflation of about 1.5% while keeping the trade balance almost constant. Competitive devaluations have, therefore,

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\(^{22}\) Countries often wish to diminish their reliance on imports of certain commodities and introduce tariffs as part of an “import substitution” agenda. The US, for example, has declared the reduction of its dependence on foreign oil a “strategy to increase economic growth and reduce vulnerability.”
vastly heterogeneous aggregate effects depending on a country’s prevalent import intensity regime, with more vertical specialization decidedly influencing the transmission mechanisms of monetary policy in open economies.

1.6 Conclusion

This paper exploits a recent competitive devaluation in Japan as a laboratory for estimating its effects on firm dynamics and aggregate outcomes. I use the fact that Abenomics constituted a novel policy response to persistent economics problems together with heterogeneity in import intensities and differential exposure to exchange rate movements across firms for identification. For the sample of public companies, the average import content of production across industries is 13% and the standard deviation is about 8%. Empirical analysis shows that Japanese exporters shrink relative to nonexporters in terms of their employment (5%), domestic sales (15%) and market capitalization (10%). The results are particularly strong when comparing the two types of firms within industries that rely more heavily on imported intermediate inputs.

Conventional open economy macro models are too simplistic in their microstructure to explain these findings. This paper develops a theoretical framework to make sense of the empirical regularities and understand the transmission mechanism of competitive devaluations in open economies. In particular, a New Keynesian two-country model augmented by three key ingredients that have been well-known in the international trade literature—heterogeneous firms, varying intermediate input intensities, and international dollar pricing—is qualitatively successful in matching the main cross-sectional patterns and the evolution of net exports as well as CPI. The quantitative fit of the model is greatly improved by a fourth ingredient that has been prominent in studies of exchange rate pass-through: strategic complementarities in firm price setting.
This paper is the first to use microdata for studying the transmission mechanisms of competitive devaluations, or currency wars. Contrary to conventional wisdom, the results suggest that such exchange rate policies end up working through “import substitution” rather than “export-led” expansions or the promotion of national export champions, thereby helping a very different set of firms than suggested by traditional open economy macro models. While the U.S. reaps additional benefits through its insulation from other countries’ nominal devaluations in a world of international dollar currency pricing, expansionary monetary policy in other open economies effectively reallocates resources toward less productive domestic companies.
Appendix

I. Variable Definitions

This list includes the main variables used throughout the analysis. All components are drawn from the merged Worldscope (WS), Capital IQ, and ORBIS annual and segment files. Variables are listed in alphabetical order.

- **Age_{i,t}**: Calculated from incorporation date (field 18272 in WS).
- **Assets_{i,t}**: Total assets (field 2999 in WS).
- **Cash/Assets_{i,t}**: Cash and equivalents (field 2001 in WS) divided by Assets.
- **Employment_{i,t}**: The number of both full and part time workers (field 7011 in WS).
- **IC_{j}**: Import content of production for any given STAN industry \( j \) (OECD).
- **Leverage_{i,t}**: Total debt as a % of Assets (field 8236 in WS).
- **Market Capitalization_{i,t}**: Market price at year end * common shares outstanding (field 8001 in WS).
- **PB_{i,t}**: Market-to-Book ratio, calculated as: \([\text{Market value of common equity (field 7210) + Assets (field 2999 in WS) + Book value of common equity (field 7220 in WS)}]/\text{Assets (field 2999 in WS)}\) [all in U.S. dollars].
• **ROA}_{i,t}: Return on assets (profitability ratio), measured as: \[
\frac{\text{Net income} - \text{Bottom line} + (\text{Interest expense on debt-interest capitalized}) \times (1-\text{Tax rate})}{\text{Average of last year’s and current year’s total assets}} \times 100
\] (field 8326 in WS).

• **Sales}_{i,t}: Total revenues generated in Japan. Sourced from the company’s geographic segment data (fields 19601–19691 in WS).

• **Size}_{i,t}: Natural logarithm of Assets.

A documented problem with ORBIS data is that key variables, such as employment, are missing once the data are downloaded. There are many reasons for this. Employment, for instance, is not reported as a balance sheet item but in memo lines. Less often, there can be other missing variables such as capital or assets. Variables are not always reported consistently throughout time in a particular disk or in a web download, either from the BvD or the Wharton Research Data Services (WRDS) website. BvD has a policy by which firms that do not report during a certain period are automatically removed from later vintages, creating an artificial survivorship bias in the sample. An additional issue is that any online download (BvD or WRDS) will cap the number of firms that can be downloaded in a given period of time. This cap translates into missing observations in the actual download task rather than termination of the request.

I implement a comprehensive data collection procedure to address these problems and maximize the coverage of firms and variables for Japan over time\textsuperscript{23} The general strategy is to merge data for Japan by downloading them from the ORBIS interface in limited search requests and making sure no information on employment or assets is discarded throughout the process.

\textsuperscript{23}Kalemli-Ozcan et al. (2015) offer a detailed analysis of how to construct representative firm-level data using the ORBIS data set.
1.A Bibliography


Table 1.1: Summary Statistics

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Note: Summary statistics are based on a snapshot of the yearly combined Worldscope and Capital IQ data sets of public and private firms in 2012.

(b) Private Companies

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Note: Summary statistics are based on a snapshot of private firms in the yearly ORBIS Bureau van Dijk Electronic Publishing (BvD) database as of 2012.
Figure 1.1: Aggregate Quantities

(a) Trade Balance

(b) GDP and Consumption Growth

Note: Panel (a) shows the USDJPY exchange rate as well as total exports and imports in yen over time; Panel (b) shows yearly real GDP as well as household consumption expenditure growth from 2008 to 2015.
Figure 1.2: Aggregate Prices

(a) Price Indexes

(b) Wage Indexes

Note: Panel (a) shows the yen-based export, import and consumer price indexes over time; Panel (b) shows the nominal and real wage indexes over the same period.
Figure 1.3: **Entry into Foreign Sales**

(a) Fraction of Firms with Foreign Sales

(b) Entrants’ Foreign Sales Volume

Note: Panel (a) displays the number of firms with positive foreign sales divided by the total number of firms over time as well as the USDJPY nominal exchange rate. Panel (b) shows the fraction of foreign sales volume generated by the 2013 entrants cohort over time.
### Table 1.2: Exporters versus Nonexporters

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<tr>
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</tr>
<tr>
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<td>–</td>
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**Note:** This table regresses the treatment status (equal to 1 for exporters) on various firm-level characteristics over the period from 2010 until 2015. Columns (1)–(3) limit attention to the subsample of public firms; columns (4)–(6) include all public and private firms. Standard errors [in brackets] are clustered at the firm-level to allow for serial correlation across time. ***,**, * indicate significance at the 1%, 5% and 10% levels, respectively.
Figure 1.4: Cross-Sectional Results

(a) Public Firms

(b) All Firms

Note: These figures plot the estimated $\psi_t$ coefficients of equation 1.1 for employment, domestic sales and market capitalization as the outcome variables with 95% confidence intervals around them. Time is measured in years and the vertical red line marks the beginning of Abenomics. Panel (a) presents the results for the subsample of public firms; Panel (b) shows the results for the whole sample of private and public companies.
Table 1.3: Mechanism

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<tr>
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</table>

Observations 66,890 65,761 66,890 65,761
Number of firms 33,445 32,907 33,445 32,907
$R^2$ 0.064 0.067 0.458 0.457

Note: This table presents triple-difference estimates of the response of employment and domestic sales for exporters versus nonexporters conditional on operating in relatively import intensive or unintensive industries. The controls in $X_{i,t-1}$ include lagged size (log total assets), leverage, the cash-to-assets ratio, as well as the interaction of each variable in $X_{i,t-1}$ with the Abenomics ($QE_t$) time indicator. Standard errors [in brackets] are clustered at the firm-level to allow for serial correlation across time. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.
Table 1.4: Mechanism in Calibrated Model

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Observations 1,200 1,200 1,200
Number of firms 600 600 600
$R^2$ 0.998 0.987 0.979

Note: This table presents model based triple-difference estimates of the response of employment, domestic sales, and prices for exporters versus nonexporters conditional on operating in relatively import intensive or un-intensive industries following a 30% yen devaluation. Standard errors [in brackets] are clustered at the firm-level to allow for serial correlation across time. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.
Figure 1.5: Mechanism

(a) Triple Difference

Note: Panel (a) plots the estimated $\zeta_t$ coefficients of equation 1.3 for employment and domestic sales as the outcome variables with 95% confidence intervals around them. Panel (b) shows the 8-year yield on JGBs, a security class that was heavily targeted during the QE interventions, and the USDJPY exchange rate. Time is measured in years and the vertical red line marks the beginning of Abenomics.
### Table 1.5: Calibration Values

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### Table 1.6: Comparison of Models

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*Note: This table lists key moments (growth rates) in the data and compares them with simulations in different versions of the model, starting from the Mundell–Fleming producer currency pricing case with no firm heterogeneity or intermediate imported inputs. Key ingredients are then added one-by-one. The numerical results assume a 30% nominal devaluation, which corresponds to the general patterns observed in Japan by 2014.*
Figure 1.6: Mundell–Fleming

(a) Firm-Level Patterns

(b) Aggregate Patterns

Note: Panel (a) displays micro firm-level reactions for prices, profits, sales and employment (in red squares). The nominal devaluation (from 0% to 50%) is displayed on each horizontal axis; the percentage change of each outcome variable relative to its normalized starting point is shown on the vertical axes. Panel (b) shows aggregate reactions for the price index (CPI), the trade balance to pre-shock GDP, exports in yen, and imports in yen (in black crosses). Again, the percentage nominal devaluation is measured on the horizontal axis in each graph.
Figure 1.7: DCP with Heterogeneous Firms

(a) Firm-Level Patterns

(b) Aggregate Patterns

Note: Panel (a) displays micro firm-level reactions for prices, profits, sales and employment for nonexporters (blue circles) and exporting firms (in red squares). The nominal devaluation (from 0% to 50%) is displayed on each horizontal axis; the percentage change of each outcome variable relative to its normalized starting point is shown on the vertical axes. Panel (b) shows aggregate reactions for the price index (CPI), the trade balance to pre-shock GDP, exports in yen, and imports in yen (in black crosses).
Figure 1.8: Kimball with Heterogeneous Firms

(a) Firm-Level Patterns

(b) Aggregate Patterns

Note: Panel (a) displays micro firm-level reactions for prices, profits, sales and employment for nonexporters (blue circles) and exporting firms (in red squares). The nominal devaluation (from 0% to 50%) is displayed on each horizontal axis; the percentage change of each outcome variable relative to its normalized starting point is shown on the vertical axes. Panel (b) shows aggregate reactions for the price index (CPI), the trade balance to pre-shock GDP, exports in yen, and imports in yen (in black crosses).
Chapter 2

The Effects of Quantitative Easing on Bank Lending Behavior

This chapter is co-authored with Oliver Darmouni.

2.1 Introduction

What are the effects of unconventional monetary policy, and how does its transmission mechanism work? These questions began to attract ever more attention during the wake of the Great Recession and following a series of aggressive liquidity measures by the Fed. In a dramatic change of policy, the European Central Bank (ECB) lately also announced its own “expanded asset purchase program”. Meanwhile, banks play a central role in the monetary system and in facilitating economic activity as shocks to the banking sector can have real effects by reducing firm borrowing and employment (Chodorow-Reich (2014b)). Motivated by these findings, this paper explores the impact of the three rounds of large-scale asset purchases (LSAPs), colloquially known as quantitative easing (QE), on commercial bank lending in the US.

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1A version of this paper was previously presented at the University of Maryland, the Macro-Financial Modeling Winter 2016 meeting at NYU Stern, Columbia’s macro lunch workshop and Princeton’s Civitas Foundation Finance Seminar.
The effectiveness of LSAPs has been a topic of vivid debate over the last couple of years. Most recently, when the Fed phased out of QE3, policy makers, commentators and analysts around the world were hoping to distill and summarize the policy’s overall economic impact. The majority of assessments, whether positive or negative, tend to focus on some uniform macroeconomic effects, including a fall in long-term interest rates, changes in confidence and inflation expectations. However, assessing policy success is made difficult by the absence of a control group which would be unaffected by the policy at such macro levels. Proponents of QE usually praise the Fed for raising asset prices and lowering yields on US Treasuries or mortgage-backed securities (MBS). Overall levels of confidence are seen to have improved, leading to greater borrowing and spending decisions on behalf of consumers. The aggregate post-crisis recovery, it is argued, came about a lot more promptly than it would have done without QE. On the other side of the debate, skeptics see QE as having fueled asset bubbles, which led to a build-up of excessive risk-taking and encouraged investors to seek refuge in questionable investments as they increasingly chose to “reach for yield”. Besides, critics have pointed to the last round of asset purchases as being inadequate and failing to raise inflation expectations. An ever improving state of the economy around 2013 was therefore seen as entirely unrelated to the Fed’s last round of quantitative easing.

This paper is the first to provide evidence on LSAPs stimulating lending by banks with considerable holdings of mortgage-backed securities on their books. Using a difference-in-differences identification strategy, banks with relatively larger holdings of MBS are shown to have expanded lending after the first and third rounds of quantitative easing (QE1 and QE3). On the other hand, QE2 had no significant influence on credit provision as it focused exclusively on Treasuries that are sparsely held by banks. Contrary to conventional wisdom, the novel takeaways consist in recognizing large heterogeneous effects of QE across lending institutions and the targeted asset’s centrality for the transmission mechanism of unconventional monetary policy.

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The paper starts out by empirically documenting commercial banks’ exposure to the Fed’s large-scale asset purchases of mortgage-backed securities. Aggregating individual bank data to the bank holding company (BHC) level from 2008Q1 until 2014Q1, each institution’s sensitivity towards QE is captured by the MBS-to-Assets ratio. In order to minimize endogeneity, and even though banks’ security holdings are remarkably sticky over time, banks are classified according to their MBS holdings in 2008Q1, which is more than a half-year before the first wave of QE. This measure of exposure is characterized by substantial cross-sectional variation across banks: while the median fraction of banks’ assets held as agency MBS is 5%, this number stands at 12% for the upper quartile.

Exploiting this cross-sectional variation to estimate the effect of quantitative easing via a standard difference-in-differences approach, we find strong and significant effects of QE1 and QE3 on the lending behavior of bank holding companies with a large share of MBS relative to their counterparts. The former group increases levels of lending by about 3% after QE1 compared to banks with little exposure, and about 2% after QE3. In contrast, QE2 focused on Treasuries and exerted virtually no differential impact on lending institutions.

Accounting for the legal restrictions governing asset purchases by the Fed as well as its declared objectives of providing support to housing markets and fostering improved financial conditions more generally, the cross-sectional variation of the MBS-to-Assets ratio across banks was orthogonal to the evolution of each institution’s pre-intervention lending rates. And while the allocation of relative MBS holdings is unlikely to be random but instead reflects diverse securitization activity and specialization in real-estate lending (as confirmed by Erel et al. (2013)), a serious effort is made to address this issue both via conditioning on a number of relevant differences among banks as well as through a matching approach to adjust the data before carrying out additional parametric analysis. With the aid of non-parametric pre-processing using standard probit models, the latter matching methodology permits to weaken the link between a bank’s treatment status and other covariates. This effectively restricts attention to a select group of matched treatment and control institutions,
with evidence from this sample being supportive of a parallel trends assumptions in lending outcomes for diverse groups of banks before the onset of QE. In other words, while the levels of lending are markedly different across treated and untreated banks throughout all time periods, there is no reason for the gap between both groups to have widened in the absence of the Fed’s interventions.

The paper also considers a myriad of robustness checks to allow for the possibility of time-varying heterogeneity across differentially exposed groups of banks. Extant research documents a “narrow channel” of QE, solely affecting the prices of each particular asset being purchased and thereby lends additional support to the main identification strategy.\footnote{Krishnamurthy and Vissing-Jorgensen (2013) argue that QE does not work via broad channels affecting the term premium on all long term bonds, but instead decreases mortgage interest rate spreads whenever targeted at MBS.} Next, a placebo analysis covering the post-2001 recession boom period finds no significant differences in lending outcomes for banks with heterogeneous MBS exposure. Finally, to fully account for borrower-level shocks that could potentially confound any bank-level findings, the Call Reports are hand-matched with Dealsean loan-level data on commercial and industrial loans to estimate the effect of QE including borrower fixed effects. This setup allows to discern whether banks with larger holdings of MBS are more likely to lend to the same firm relative to other institutions and confirms the original bank-level findings.

We carefully explore two relevant channels by which large-scale asset purchases could exert influence on banks’ proclivity to lend via a balance sheet improvement. The first channel is the “net worth channel”: when asset purchases have a large impact on security prices, the policy increases the mark-to-market value of bank security holdings and in turn raises bank net worth, a mechanism recently labeled as “stealth recapitalization” by Brunnermeier and Sannikov (2014). We find this net worth channel to be at play during QE1, but not during the following waves of QE, consistent with previously established results about later rounds of QE having a smaller impact on MBS prices. In line with this view, we find that treated banks expanded assets and experienced gains on their security holdings only after
QE1. On the other hand, QE3 appeared to have worked through a “liquidity channel”: as MBS became more liquid, banks could swap them for reserves and expand their lending. Additional illiquidity coming from more lending is mitigated by extra liquidity on the rest of the asset side. Our results reveal that there are multiple channels by which this supplementary liquidity created by QE can be used within the banking sector.

### 2.2 Relation to the Literature

This paper is primarily related to the literature on the bank lending channel of monetary policy transmission (Kashyap and Stein (1994)). Seeking to find evidence that monetary policy affects the economy via credit supply, the bank lending channel posits a failure of the Modigliani-Miller theorem for banks. In line with these arguments, Kashyap and Stein (1995) show that monetary tightening reduces lending by relatively small banks. Analogously, Campello (2002) provide evidence that contractionary monetary policy reduces the amount of loans made by banks that are unrelated to a large banking group. Kashyap and Stein (2000) elucidate the same mechanisms for banks that hold fewer liquid assets, while Kishan and Opiela (2000), Gambacorta and Mistrulli (2004) carry out the analysis for banks with higher leverage ratios. More recent work investigates a risk-taking channel, where reductions in policy rates cause financial institutions to take on larger risks and result in lower risk premia (Adrian and Shin (2010a), Borio and Zhu (2012)). Focusing on the income gap, a measure of banks’ cash flow exposure to interest rate risk, Landier et al. (2015) document its pivotal role for the lending behavior of banks following monetary policy shocks.

Another proximate branch of literature concerns the liability structure of banks during periods of liquidity shocks. Dagher and Kazimov (2015) use loan-level data to show that banks end up curtailing their lending by more if they are heavily reliant on wholesale funding during crises. Ivashina and Scharfstein (2010) demonstrate that banks cut less of their lending during the 2008 crisis if they had better access to deposit financing and were less
dependent on short-term debt. The broader work studying the impact of liquidity shocks on credit supply includes Puri et al. (2011), Paravisini (2008), Peek and Rosengren (2000), and Cornett et al. (2011). A recent extension of the Khwaja and Mian (2008) methodology in loan-level regressions to isolate credit supply devised by Jiménez et al. (2014) to identify aggregate firm-level effects through credit shocks is also taken up in the present study.

This research is also related to a strand of theoretical work emphasising the sharply non-linear effects of financial sector capital on risk premia and lending (He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014)). In these models, large contractions in financial sector capital lead to binding borrowing constraints or adverse feedback loops. In a fire sale, the pressure to delever decreases mark-to-market prices of assets held at other institutions, leading to further deleveraging (Shleifer and Vishny (2011)). The focus on liquidity management issues interacted with monetary policy shocks and lending choices is closely linked to the agenda of Bianchi and Bigio (2014).

Part of the mechanism uncovered in this paper is the empirical analogue of redistributive monetary policy, as first introduced by Brunnermeier and Sannikov (2015). In their model, monetary policy impacts the real economy by affecting the value of assets held by agents on their books. For instance, raising the price of a long-term security effectively improves the balance sheets of agents who hold this asset and relaxes financial constraints. In other words, such policy is equivalent to a stealth recapitalisation of these agents. The key aspect is that not all agents in this economy are affected in the same way: heterogeneity in asset holdings matters for aggregate outcomes and policy makers should choose carefully which asset to buy instead of simply focusing on quantity, an insight which the present study is first to uncover empirically.

This mechanism is akin to the net-worth channel developed in Bernanke and Gertler (1989), Kiyotaki and Moore (1997), and Bernanke et al. (1999). Unconventional monetary policy raises the prices of MBS held as assets and leads to an improvement in the mark-to-market value of bank equity. Assuming that commercial banks target constant leverage
ratios (Adrian and Shin (2010b)), these changes induce banks to expand their lending and take on additional debt.

The nascent literature studying the effects of LSAPs is also very much related to this paper. The high-frequency event study by Chodorow-Reich (2014a) suggests that the Fed’s unconventional monetary policy actions had a strong positive impact on banks and life insurance companies by raising the value of their legacy assets in 2008. Krishnamurthy and Vissing-Jorgensen (2013) examine the influence of quantitative easing on asset prices and interest rate spreads. Morais et al. (2015) provide some first evidence on the international dimensions of QE, documenting credit supply spillovers from US and European banks to Mexico. A contemporaneous paper by looks at unconventional monetary policy in relation to re-financing and consumption choices, while another very recent paper by explores the impact of MBS purchases on the industrial organization of loan origination across regions in the US. Our focus on the total amount of credit is complementary to other papers looking at loan costs and re-financing (?; ?). Finally, this article is linked to previous work on the real effects of credit market disruptions, especially in the aftermath of the 2008 crisis (Chodorow-Reich (2014b) and Greenstone et al. (2014)).

2.3 Background of LSAPs

The initial wave of large-scale asset purchases (QE1) began on November 25, 2008 when the FOMC announced a program to purchase agency mortgage-backed securities (MBS) with the stated intentions of providing support to mortgage lending and housing markets as well as fostering improved conditions in financial markets more generally. The purchase phase was completed on March 31, 2010 after the Fed accumulated $1.25 trillion in MBS, $175 billion in federal agency debt (issued by Fannie Mae, Freddie Mac and Ginnie Mae) and $300 billion in long-term Treasury securities. At that point, the Fed’s market share of agency MBS had reached approximately 25%. While the purchase of $300 billion in long-term Treasuries
was meant to exert downward pressure on interest rates in general, the joint purchase of $1.425 trillion of MBS and agency debt was aimed at increasing credit availability in private markets, resuscitating mortgage lending and supporting the housing market.

In mid-2010, numerous concerns about a deflationary spiral led to serious fears of a lost decade of economic growth, similar to Japan’s experience during the 1990s. To avert deflation, the Federal Open Market Committee (FOMC) introduced a second round of LSAPs (QE2), entailing the total purchase of $778 billion in long-term Treasury securities, which included $600 billion in announced program purchases and $178 billion as reinvestment of principal payments from the Fed’s agency debt and MBS holdings. This second round of quantitative easing lasted from November 3, 2010 until June 30, 2011 and proceeded at a pace of $75 billion per month.

With the onset of Europe’s sovereign debt crisis threatening to further destabilize the US economy, the FOMC turned to its maturity extension program, known as Operation Twist. This involved the sale of short-term Treasury securities and an equal purchase of long-term Treasury securities to exert downward pressure on long-term interest rates while maintaining the same amount of securities on the Fed balance sheet. Operation Twist was started in September 2011 and extended in June 2012 to continue through the end of 2012. Overall, the FOMC purchased, sold and redeemed $667 billion in Treasury securities through this program, dispensing all holdings of short-term securities with a maturity of one year or less.

Finally, on September 13, 2012 the FOMC began a largely unanticipated third round of quantitative easing (QE3). The purchases initially involved $40 billion in agency MBS per month. However, after Operation Twist ended in December 2012, the FOMC added $45 billion in long-term Treasury securities to the monthly purchase. And while at its December 2013 meeting, the FOMC reduced the monthly asset purchases for the first time, dropping the

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5 The extent of the Fed’s push towards recovery was a surprise to traders, prompting a rally in stocks and commodities. In particular, the Wall Street Index rose by 1.6% within two hours of the news, along with huge gains in Asian and European markets. For more: “QE3: Reactions to the Fed’s big stimulus move”, The Washington Post, September 13, 2012.
total amount to $75 billion from $85 billion, the QE3 program continued as state-contingent and open-ended initiative until October 29, 2014 when it was formally discontinued. By the end of all three QE rounds, the Fed had accumulated $1.75 trillion in MBS, representing around 30% of the entire agency MBS market.

For the analysis in subsequent sections, it is important to highlight some institutional features of the Fed’s LSAPs throughout this period. Agency MBS are generally demarcated by different coupons, corresponding to the interest rate on the underlying mortgage loans. More than 90% of agency MBS trading volume occurs in the To-Be-Announced (TBA) forward market. And while the degree of integration in the agency MBS market is quite high, the Fed’s purchases were primarily targeted at mortgage-backed securities with coupons near those of new mortgage loan originations, often called current-coupon or production-coupon MBS. These assets have greater liquidity and are closely tied to primary mortgage rates. Meanwhile, the TBA market is the most liquid, and hence the most important secondary market for mortgage loans. Market participants that benefit from TBA trading are primarily mortgage bankers, commercial banks, and thrift institutions that originate residential mortgages and sell them into the secondary mortgage market in securitized form. According to the rules of the Federal Reserve Act, only fixed-rate agency MBS guaranteed by Fannie Mae, Freddie Mac and Ginnie Mae were eligible assets for purchase, including the 30-year and 15-year securities of these issuers. The New York Fed’s primary dealers were entitled to transact in agency MBS directly with the Federal Reserve, and they were expected to submit bids or offers for themselves as well as for their customers.

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6This $10 billion reduction consisted of an equal $5 billion decline for both MBS and US Treasury security purchases.

7In a TBA trade, the buyer obtains a contract for delivery of securitized mortgage loans at some date in the future. As part of a unique feature of such contracts, the buyer is left in the dark about the actual identity of the securitized mortgage loans to be delivered. Instead, participants agree on general parameters, such as the issuer, maturity, or coupon, and the buyer discovers the actual parameters of the loan 48 hours prior to the settlement of the forward contract.
2.4 Data and Empirical Strategy

2.4.1 Data Construction

This paper mainly relies on two datasets: i) the Consolidated Reports of Condition and Income (Call Reports), formally known as the FFIEC 031 and FFIEC 041 regulatory filings, which must be submitted each quarter by all commercial banks with insured deposits and from which all main variables in the analysis are sourced, and ii) the Dealscan syndicated loan database, which contains the borrowing history of both public and private firms that have accessed the syndicated loan market. The Call Reports include detailed information on the composition of banks’ income statements, balance sheets, and off-balance sheet items. The time period under consideration in this study spans the main period of LSAPs, from 2008Q1 up until 2014Q1.

In line with most of the empirical literature based on the Call Reports, the raw data are adjusted to account for the fact that many banks are part of multibank holding companies. Hence individual bank data are aggregated to comprise holding-company level financial information. That is, any given bank in the sample is really a holding company which does not include any of its non-bank subsidiaries, as these are excluded from the Call Reports. An effort is made to minimize the number of excluded banks and thereby avoid any sample-selection biases. Following Kashyap et al. (2002), no direct conditioning on whether banks engage in mergers or acquisitions is carried out in the regression models below, even though the continuous representation of separate bank entities over the whole sample period is a binding restriction in the fixed-effects specifications in sections 2.5.1 and 2.5.2. In other words, all tests are carried out with a balanced sample of bank holding companies.

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8 It is important to point out that the results are largely unaffected by working with the disaggregated data at the individual bank level.

9 As an alternative procedure to control for any possible M&A activity, restricting the entire sample to banks that have quarterly total asset growth of no more than 10% for any given banking organization yields very similar baseline results.
The loan market data come from the Thomson Reuters Dealscan database, which collects loan-level information on syndicated loans from Securities and Exchange Commission (SEC) filings, company statements, and media reports, and attempts to process the universe of such loans. The data include the identities of the borrower and lenders present at origination, the terms of the loan, the maturity, size, interest rate, type, and purpose of the loan (for example, working capital, or leveraged buyout). For the tasks in this paper, the Dealscan database is also hand-matched to the Call Reports for the 95 largest bank holding companies in the loan-level analysis of QE in section 2.5.3.

A set of dependent, independent and control variables is constructed for all included bank observations. The definitions of all these variables are listed precisely in Appendix 2.7. Summary statistics are reported in Tables 3.4 and 2.2.

2.4.2 Empirical Strategy

In light of the major LSAP events described in section 2.3, this paper exploits disparities in the level of exposure towards the Fed’s interventions by grouping banks according to the relative amount of mortgage-backed securities on their balance sheets. For identification, this difference-in-differences (DiD) methodology relies upon the interaction of aggregate endogenous variation in MBS prices or purchases with sufficient cross-sectional variation among banks in their MBS holdings. Figure 3.2 plots the price series of Fannie 30–year 3% coupon MBS in Panel (a), and the prices of Fannie 30–year 5% coupon MBS in Panel (b).

The former series is representative of the targeted securities during QE3, when interest rates were already much lower than in 2008, while the latter graph is indicative of the types of assets being purchased during the first phase of LSAPs. One immediate takeaway from Panel (b) is the relatively large and persistent price effect of QE1. In line with previous findings

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10Public companies are obliged to report any new bank loan to the SEC via 8-K filings, or as an attachment to their quarterly or annual reports. The public ranking of lender activity in the syndicated loan market assembled by Thomson Reuters on the basis of Dealscan is thought to provide banks with additional incentives to report loans, which Dealscan might otherwise have missed. Loans with a single lead arranger and zero participants are usually somewhat larger than other loans in the dataset.
Figure 2.1: MBS Prices
Note: Panel (a) shows the Fannie 30-year 3% Coupon MBS price series; Panel (b) displays the Fannie 30-year 5% Coupon MBS price graph. Events related to QE1, QE2, and QE3 are delineated by vertical red lines.
Table 2.1: Panel A: Summary Statistics (Call Reports)

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<td>0.13</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>160606</td>
</tr>
<tr>
<td>realised gains / assets</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>160606</td>
</tr>
<tr>
<td>unrealised gains / assets</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>160606</td>
</tr>
</tbody>
</table>

Note: Summary statistics are based on the Consolidated Reports of Condition and Income (Call Reports) between 2008Q1 – 2014Q1 for all US bank holding companies excluding their non-bank subsidiaries. All variables are quarterly.

Table 2.2: Panel B: Summary Statistics (Dealscan)

<table>
<thead>
<tr>
<th>Sample</th>
<th>Δ log(lending)</th>
<th>renewal dummy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample</td>
<td>mean</td>
<td>sd</td>
</tr>
<tr>
<td>whole</td>
<td>-7.1</td>
<td>8.7</td>
</tr>
<tr>
<td>median treatment</td>
<td>-5.8</td>
<td>8.33</td>
</tr>
<tr>
<td>quartile treatment</td>
<td>-6.05</td>
<td>8.41</td>
</tr>
<tr>
<td>decile treatment</td>
<td>-6.08</td>
<td>8.41</td>
</tr>
</tbody>
</table>

Note: Summary statistics are based on the Dealscan flow data.

by [Krishnamurthy and Vissing-Jorgensen (2013)](https://example.com), the Fed programs seemed to operate via a “narrow channel”, with no clear MBS price impact of QE2. The response of prices to QE3 is visible but a lot more modest than the one observed after QE1, both in terms of magnitude and life span, which is not surprising given the substantially slower pace of MBS purchases during QE3.

It should be pointed out, however, that commercial banks held approximately 26% – 30% of total agency MBS outstanding over the period from September 2013 until December.
Table 2.3: Transition matrices

<table>
<thead>
<tr>
<th></th>
<th>Treatment by quartiles</th>
<th>Treatment by median</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$T_i = 0$</td>
<td>$T_i = 1$</td>
</tr>
<tr>
<td>$T_i = 0$</td>
<td>99.82</td>
<td>0.18</td>
</tr>
<tr>
<td>$T_i = 1$</td>
<td>0.19</td>
<td>99.81</td>
</tr>
</tbody>
</table>

Note: These tables contain transition probabilities for being classified as belonging to the treatment group (defined either by the upper quartile or above the median MBS-to-Assets holdings) between 2008Q1 and 2014Q1.

2014\textsuperscript{11} and hence one should still expect a sizeable liquidity effect from the Fed’s LSAPs, as will be confirmed below when looking at the effects on realized gains on available-for-sale securities for relatively exposed commercial banks.

The cross-sectional variation in MBS holdings across banks, defined by their MBS-to-Assets ratio, is also large during all periods under consideration. From the summary statistics reported in Table 3.4 one can see that the MBS-to-Assets ratio has a standard deviation of 0.10 and mean value of 0.08\textsuperscript{12}. Moreover, there are institutions for which this variable is either zero or close to 0.83. Figure 3.3 displays a histogram for the entire distribution of the MBS-to-Assets and MBS-to-Securities ratios in the sample during the cutoff period before QE1, which is in 2008Q1.

In most baseline specifications, the impact of quantitative easing is assessed via difference-in-differences regressions that define banks from the lowest 25\% of the MBS-to-Assets distribution as the control group (C) and institutions among the highest 25\% of the sample as the treatment group (T). We also report results using the MBS-to-Assets ratio as a continuous variable, which allows for an analysis of the entire sample of banks. Moreover, as displayed in the transition matrices in Table 2.3 banks are extremely rigid in their relative MBS-to-Assets holdings over time, with very little movement in the re-calculated treatment assignments from quarter to quarter. This alleviates the concern that banks anticipate or

\textsuperscript{11}Source: Federal Reserve, Flow of Funds.

\textsuperscript{12}An alternative is to sort banks according to their MBS-to-Securities ratio (standard deviation of 0.31 and mean of 0.35). Unreported specifications use this alternative definition for robustness.
strategically respond to QE by adjusting their holding of mortgage-backed securities over time.

Nevertheless, banks with higher than median MBS holdings are distinct along a number of important observable characteristics. Table 2.4 tests whether treated banks are in fact systematically different from their counterparts. As a fraction of their assets, banks with a relatively high MBS-to-Assets ratio as of 2008Q1 are similar to the control group in terms of lending over the entire time period. However, treated banks are typically bigger, hold more securities as a share of assets, and are slightly less profitable on average. This implies that all regressions should control for these main disparities, such as size and other balance sheet items pertinent to bank lending decisions.
Table 2.4: Correlation between Treatment and Initial Characteristics

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$Treat_i^D$</td>
<td>$Treat_i^Q$</td>
<td>$(MBS_{Assets})_i$</td>
</tr>
<tr>
<td></td>
<td>coeff</td>
<td>s.e.</td>
<td>coeff</td>
</tr>
<tr>
<td>log(assets)</td>
<td>$0.081^{***}$</td>
<td>$[0.009]$</td>
<td>$0.099^{***}$</td>
</tr>
<tr>
<td>liabilities / assets</td>
<td>$-0.016$</td>
<td>$[0.233]$</td>
<td>$-0.049$</td>
</tr>
<tr>
<td>securities / assets</td>
<td>$1.317^{***}$</td>
<td>$[0.127]$</td>
<td>$1.596^{***}$</td>
</tr>
<tr>
<td>deposits / assets</td>
<td>$0.216$</td>
<td>$[0.191]$</td>
<td>$0.209$</td>
</tr>
<tr>
<td>borrowing / assets</td>
<td>$1.023^{***}$</td>
<td>$[0.254]$</td>
<td>$0.929^{***}$</td>
</tr>
<tr>
<td>reserves / assets</td>
<td>$0.258$</td>
<td>$[0.134]$</td>
<td>$0.358^{*}$</td>
</tr>
<tr>
<td>lending / assets</td>
<td>$-0.184$</td>
<td>$[0.108]$</td>
<td>$0.138$</td>
</tr>
<tr>
<td>r. gains / assets</td>
<td>$22.59$</td>
<td>$[19.34]$</td>
<td>$41.65$</td>
</tr>
<tr>
<td>u. gains / assets</td>
<td>$-2.833$</td>
<td>$[3.013]$</td>
<td>$-0.961$</td>
</tr>
<tr>
<td>duration gap</td>
<td>$0.0009$</td>
<td>$[0.001]$</td>
<td>$0.0007$</td>
</tr>
<tr>
<td>ROA</td>
<td>$-2.954^{*}$</td>
<td>$[1.168]$</td>
<td>$-4.608^{**}$</td>
</tr>
<tr>
<td>$N$</td>
<td>1594</td>
<td>2588</td>
<td>5148</td>
</tr>
<tr>
<td>adj.$R^2$</td>
<td>0.471</td>
<td>0.370</td>
<td>0.380</td>
</tr>
</tbody>
</table>

Note: This table regresses the treatment status defined by the decile of MBS-to-Assets holdings (column 1), quartile (column 2), and the continuous MBS-to-Assets measure (column 3) on bank characteristics in 2008Q1, and reports the coefficient and standard errors for each variable. Standard errors are clustered at the bank-level and displayed in brackets. $^{***}$, $^{**}$, $^{*}$ indicate significance at the 1%, 5% and 10% levels, respectively.

To reduce potential biases in estimating the causal effects stemming from the endogenous determination of MBS holdings among bank holding companies themselves, all baseline specifications will use a standard propensity score matching approach. At first, a probit model is estimated to predict a bank’s treatment status on the basis of major bank-level characteristics used in the pooled regressions before the QE interventions in 2008Q1. Next, the predicted values from this probit regression (propensity scores) are employed to construct a nearest-neighbor matched sample of banks. While matching each high MBS-holding institution to a control bank with replacement, this approach effectively discards untreated observations that end up being too different based on observables from the treatment group. 

---

13 Since certain institutions end up being matched with several treated banks more than once, the second step entails retaining the frequency weights from the above matching procedure for each undiscarded control bank. In order to have a sample of banks consistent across all specifications, control and treatment groups are defined according to median MBS-to-Assets holding in the matching procedure. It should be pointed out that using the whole *unmatched* sample of banks leaves all baseline regressions and robustness test largely unchanged in terms of the magnitude and statistical significance of our main findings.
Table 2.5: Propensity Score Matching

<table>
<thead>
<tr>
<th></th>
<th>$Treat_i$ (1)</th>
<th>$Treat_i$ (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Size$</td>
<td>0.211***</td>
<td>-0.004</td>
</tr>
<tr>
<td></td>
<td>[0.015]</td>
<td>[0.024]</td>
</tr>
<tr>
<td>$Equity$</td>
<td>0.107</td>
<td>-0.271</td>
</tr>
<tr>
<td></td>
<td>[0.212]</td>
<td>[0.306]</td>
</tr>
<tr>
<td>$ROA$</td>
<td>-3.802*</td>
<td>-6.071</td>
</tr>
<tr>
<td></td>
<td>[2.256]</td>
<td>[4.559]</td>
</tr>
<tr>
<td>$Constant$</td>
<td>-2.509***</td>
<td>0.090</td>
</tr>
<tr>
<td></td>
<td>[0.185]</td>
<td>[0.294]</td>
</tr>
<tr>
<td>Matching Observations</td>
<td>pre--</td>
<td>post--</td>
</tr>
<tr>
<td></td>
<td>5,152</td>
<td>5,186</td>
</tr>
<tr>
<td>$p$-value</td>
<td>0.00</td>
<td>0.509</td>
</tr>
</tbody>
</table>

Note: This table presents coefficient estimates from probit regressions used in estimating the propensity scores for the treatment and control group of banks in 2008Q1. The dependent variable is a bank’s treatment status; the controls include Size (log total assets), equity over assets, and return on assets (ROA). Column (1) contains estimates using the entire sample prior to matching; this model generates the propensity scores. Column (2) uses the subsample of treated and control banks after matching. Standard errors are in brackets. ***,**,* indicate significance at the 1%, 5% and 10% levels, respectively.

The following test is conducted to assess the quality of the matching procedure. In particular, the probit model is re-estimated on the matched sample of banks and the results are reported in Table 2.5. Compared to the pre-match probit regression that was used to perform a nearest-neighbor propensity score matching, and for which the estimates are presented in column (1), the magnitude of all probit regression coefficients declines substantially using the post-match model in column (2). In fact, none of the main dimensions of heterogeneity continue to play any role in explaining the treatment status across banks, whereas both size and profitability were statistically significant in the pre-match sample before. Furthermore, the $\chi^2$ test for overall model fit shows that one cannot reject the null hypothesis that all coefficient estimates are zero: the $p$-value equals 0.51 in column (2). Thus, the matching
process removes meaningful differences along observable dimensions between the two groups of banks.

In an initial attempt to eye-ball the main data and outcome variables, Figure 3.4 plots the Federal Reserve Holdings of Treasury Notes (long-dashed green) and Mortgage-Backed Securities (dashed blue) from 2008Q1 until 2014Q1, all measured on the right vertical axis in billions of US dollars. The figure also shows the average lending-to-assets ratios for treated banks in the upper quartile of MBS-to-Assets holdings (T group, in solid black) versus the lower quartile (C group, in dashed gray). These lending ratios are measured on the left vertical axis. The vertical lines and shaded areas mark the QE1, QE2 and QE3 periods.
2.5 Results

2.5.1 Pooled regressions

Although Figure 3.4 contributes some preliminary evidence in favor of a positive liquidity shock stemming from the Fed’s interventions, as the gaps in lending-to-assets ratios seem to narrow around QE1 and QE3, the presence of a lending channel cannot be taken for granted as banks with higher fractions of MBS holdings might differ systematically from their peers. For instance, banks with a higher exposure towards LSAPs may be lending to firms that experience faster credit demand growth due to improvements in their borrower health around the same time period. If this were true, the bank-level analysis would be spuriously driven by credit demand shocks and the results would be misattributed to the Fed’s QE policies. To address these concerns, section 2.5.3 devotes attention to C&I loan issuance data from Dealscan, implementing the Khwaja and Mian (2008) (KM) within-firm estimator to absorb firm fundamental shocks that proxy for a company’s level of credit demand.

The initial regression framework to gauge the causal effects of QE consists of looking at average lending outcomes following each of the QE waves. The following pooled model is estimated:

\[
\log(Y_{i,t}) = \alpha_i + \gamma' \text{QE}_t + \delta' (\text{Treat}_i \cdot \text{QE}_t) + \theta' X_{i,t} + \lambda' X_{i,t} \cdot \text{QE}_t + \nu_{i,t} \tag{2.1}
\]

where \(Y_{i,t}\) is the level of either total, real estate, or C&I lending, \(\alpha_i\) is a bank fixed effect, \(\text{Treat}_i\) is an indicator variable equal to 1 whenever a bank belongs to the treatment group as defined by the upper quartile and 0 if the institution belongs to the lower quartile of the MBS-to-Assets distribution prior to QE1, \(\text{QE}_t = \{Q_{E1t}, Q_{E2t}, Q_{E3t}\}\) is a set of indicator variables which become equal to 1 after the introduction of each QE episode, and \(\text{Treat}_i \cdot \text{QE}_t\) is an interaction term between the QE dummies and a bank’s treatment status. Following

\[\text{In an earlier version of the paper, each QE round was considered in a separate difference-in-differences model around the respective cutoff dates. The results are even stronger than the ones using the pooled specification. We use the latter for ease of exposition and magnitude comparisons across all QE waves.}\]
the literature on bank lending (e.g. Kashyap and Stein (2000)), the matrix of controls, \(X_{i,t}\), includes bank size, equity normalized by total assets, and return on assets (ROA) as a benchmark for profitability. In order to control for maturity mismatch, we also include the duration gap measure introduced by English et al. (2014)\(^{15}\). As a further robustness check on the identification strategy, all control variables are interacted with the \(QE_t\) indicators to allow for possible heterogeneous responses to the intervention by bank holding companies of different nature. All standard errors are clustered at the bank level to allow for serial correlation across time.

The key parameters of interest are the elements of \(\delta\) as they capture the difference in lending outcomes between banks with relatively high and low mortgage-backed security (MBS) portfolios after each of the QE shocks. In other words, \(\delta\) measures the treatment effect of each wave. Table 2.6 reports the results after estimating equation 2.1 for quarterly lending from 2008 to 2014. The first two columns consider the effect on total lending. Column (1) defines treatment and controls as the top and bottom quartile of the MBS-to-Assets holding distribution in 2008Q1, while column (2) uses the continuous MBS-to-Assets measure also before QE1\(^{16}\). Across all specifications, we find a positive and robustly statistically significant effect of both QE1 and QE3. The last four columns reveal that the effect is primarily driven by an expansion in real estate lending (which is 55% of all loans), while corporate lending increases somewhat less strongly.

With the natural logarithm of lending as the dependent variable, these estimates suggest QE1 boosted lending of treated banks by about 3% relative to the control group. The estimated effect of QE3 is about 2%, although, as indicated by the \(p\)-value in the last row of Table 2.6, the difference between both coefficients is not always statistically significant. The

\(^{15}\)This paper uses Call Report data to construct a new, more refined measure of the mismatch between the repricing time or maturity of assets and liabilities at the individual bank level. While most of the literature has considered the share of assets and liabilities that mature or reprice within a year, the considerably more granular measure used in this paper constructs a weighted average of maturity for multiple categories of assets and liabilities and defines the maturity/repricing gap as the difference between the two. For more details, see English et al. (2014)

\(^{16}\)In non-parametric versions of the model, linearity seems to be a reasonable approximation. Also, the continuous measure has the additional benefit of using all observations in the sample.
Table 2.6: Pooled QE Regression

<table>
<thead>
<tr>
<th></th>
<th>log($Lending_{it}$)</th>
<th>log($RE Lending_{it}$)</th>
<th>log($CI Lending_{it}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>$Treat_{M,i} \cdot QE_{1t}$</td>
<td>0.034***</td>
<td>0.047***</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>[0.008]</td>
<td>[0.009]</td>
<td>[0.028]</td>
</tr>
<tr>
<td>$Treat_{T,i} \cdot QE_{2t}$</td>
<td>0.028</td>
<td>-0.008</td>
<td>0.034</td>
</tr>
<tr>
<td></td>
<td>[0.018]</td>
<td>[0.014]</td>
<td>[0.037]</td>
</tr>
<tr>
<td>$Treat_{M,i} \cdot QE_{3t}$</td>
<td>0.017**</td>
<td>0.021**</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>[0.008]</td>
<td>[0.010]</td>
<td>[0.039]</td>
</tr>
<tr>
<td>($\frac{MBS}{Asset}$)$<em>{i} \cdot QE</em>{1t}$</td>
<td>0.178***</td>
<td>0.248***</td>
<td>0.146</td>
</tr>
<tr>
<td></td>
<td>[0.041]</td>
<td>[0.046]</td>
<td>[0.093]</td>
</tr>
<tr>
<td>($\frac{TRE}{Asset}$)$<em>{i} \cdot QE</em>{2t}$</td>
<td>0.084</td>
<td>0.080</td>
<td>0.291</td>
</tr>
<tr>
<td></td>
<td>[0.067]</td>
<td>[0.121]</td>
<td>[0.221]</td>
</tr>
<tr>
<td>($\frac{MBS}{Asset}$)$<em>{i} \cdot QE</em>{3t}$</td>
<td>0.172***</td>
<td>0.144***</td>
<td>0.328***</td>
</tr>
<tr>
<td></td>
<td>[0.040]</td>
<td>[0.047]</td>
<td>[0.100]</td>
</tr>
<tr>
<td>$QE_t$</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Controls $\cdot QE_t$</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Bank FE$es$</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of banks</td>
<td>1,939</td>
<td>3,949</td>
<td>1,934</td>
</tr>
<tr>
<td>Observations</td>
<td>59,870</td>
<td>128,966</td>
<td>59,608</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.668</td>
<td>0.711</td>
<td>0.543</td>
</tr>
<tr>
<td>p-value</td>
<td>0.0613</td>
<td>0.879</td>
<td>0.0459</td>
</tr>
</tbody>
</table>

Note: This table presents coefficient estimates from specifications at the BHC level relating lending from 2008Q1 to 2014Q1 with banks’ initial exposure towards LSAPs, as captured by their treatment group membership or MBS-to-Assets ratio back in 2008Q1. The controls include Size (log total assets), equity over assets, return on assets (ROA), and the duration gap. $QE_t$ denotes the triple of QE indicators. The reported $p$-value tests for coefficient inequality between $QE1$ and $QE3$. Standard errors [in brackets] are clustered at the bank-level to allow for serial correlation across time. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

effect of QE2 is estimated to be zero$^{17}$ The following “back-of-the-envelope” calculation can give a sense of the magnitude of the effects. For instance, as QE3 was introduced total

$^{17}$The results are unaffected by replacing the dependent variable with the logarithm of lending-to-assets, with assets held fixed prior to the introduction of QE. In other words, the impact of QE is large and significant because treated banks see their lending expand rather than seeing their assets contract.
lending by the treated banks in 2012Q2 was about $3.4 trillion, and if one is willing to assume that the control group was completely unaffected by the policy, then the aggregate increase in bank lending would constitute about $100 billion.\footnote{It should be noted, however, that this number represents an upper bound for the aggregate effect of QE3 on lending as control banks are likely to have reduced their lending to some extent while treated banks expanded their lending.}

US Treasuries are in general a much smaller component of commercial banks’ balance sheets than mortgage-backed securities. One can see in Table 3.4 that the median level of Treasuries as a fraction of total securities is zero, while the median value of MBS as a share of securities is 32%. Moreover, the upper quartile of the MBS-to-Securities distribution is 60%, whereas it is still zero for the ratio of Treasuries-to-Securities. Given this importance of MBS relative to Treasuries, one should expect QE2 to have exerted a smaller influence on bank lending after all.

These findings provide evidence of the importance of the type of assets being purchased as part of any unconventional monetary policy intervention, as opposed to simply quantities. Since numerous commercial banks were heavily exposed to agency MBS, positive liquidity and price shocks to these particular assets led to much greater balance-sheet improvements than any intervention targeted at relatively sparsely held securities. In times when QE becomes a more frequent phenomenon around the world, these results should help in guiding policy makers’ decisions by revealing that certain financial agents would be more affected by LSAPs depending on the choice of asset.

### 2.5.2 Timing of the effects

To be plausibly driven by QE, all of the effects documented thus far need to have occurred after the policy introduction and not before. Indeed, the results might be driven by some pre-existing trend in the data, with treated banks having begun to expand their lending relative to the control group prior to the introduction of QE. In order to lend additional support to the causal interpretation of the findings, the next series of tests relies upon using
repeated observations for the same bank over time. As noted before, a balanced panel of banks is considered as a way to avoid possible M&A activity and reduce outliers.

We estimate a fixed-effects regression using the matched sample of banks. In the spirit of Granger (1969), the following specification is estimated in order to see whether causes happen before consequences and not the other way around:

\[
\log(Y_{it}) = \alpha_i + \sum_t \gamma_t D_t + \sum_t \delta_t (D_t \cdot Treat_i) \\
+ X_{it}' \theta + \sum_t \psi_t (D_t \cdot X_{it}) + \epsilon_{it}
\]

(2.2)

Here, as above, \(Y_{it}\) is the lending outcome, \(\alpha_i\) are bank holding company fixed effects, \(Treat_i\) is an indicator variable equal to 1 if a bank belongs to the upper quartile of the MBS-to-Assets distribution and 0 whenever an institution is assigned to the lower quartile, \(D_t\) is an indicator for the time period (quarter), with 2008Q1 taken as the omitted category, \((D_t \cdot Treat_i)\) represents an interaction term between the time indicators and a bank’s MBS treatment status, and \(X_{it}\) is a matrix of control variables that includes bank size, equity normalized by total assets, a measure of maturity mismatch and return on assets (ROA) as a benchmark for profitability. All standard errors are clustered at the bank-level to allow for serial correlation across time.

The main parameters of interest are \(\delta_t\) since they capture the difference between banks with relatively high and low mortgage-backed security holdings over time. The estimated model includes one observation each quarter per bank.

Figure 3.6 plots the key estimated parameters of interest, \(\hat{\delta}_t\), with 95% confidence intervals around them. As would be consistent with a differential impact of LSAPs, the estimates show no robust differences between the treated and control banks in the quarters prior to the phasing in of QE1, and increasing effects on lending after adoption. The three QE periods are
Figure 2.4: All Banks – coefficient plots
Note: These figures plot the estimated $\delta_t$ coefficients of equation 2.2 with 95% confidence intervals around them. Time is measured on a quarterly level and the vertical vermilion (dot-dashed), light-blue (dashed) and turquoise (long-dashed) lines mark the QE1, QE2 and QE3 episodes, respectively.
demarcated with dashed lines: QE1 and QE3 have a positive effect on lending given out by treated banks, while the middle period coinciding with QE2 displays no such influence. The evidence for real estate lending is particularly clean, showing widening differences between both groups of banks during and shortly after QE1, whereas the estimates for C&I loans are insignificant and add some noise to the total lending graph in Panel (a). Overall, though, even if the gaps in total lending between treated and control banks oscillate a little after the end of QE1 and before the start of QE3, these differences widen permanently at the time of MBS purchases and thereby reinforce the causal interpretation of the results from section 2.5.1.

In an effort to better understand the effects of QE, we next investigate whether small and large banks vary in their lending sensitivity with respect to unconventional monetary policy. Banks above the median of the assets distribution as of 2008Q1 are coded as “large” while institutions below this threshold are considered separately as “small”. The matching procedure is applied and the treatment allocation by quartiles is re-defined within each of these balanced sub-panels. The corresponding $\hat{\delta}_t$ parameter plots of equation 2.2 for each group are displayed in Panels (a)–(c) of Figure 3.7.

The results for total lending for the small group are sizeable, statistically significant and confirm the causal interpretation of QE through their timing. The effects on real estate lending are similar, while C&I loans remain largely unresponsive. These patterns are consistent with the notion that small banks are more likely to benefit from the balance sheet improvements due to QE, and reinforce our previous findings.

2.5.3 Loan issuance

This section addresses the issue of potential confounding demand-side factors that could be driving the results. The analytical framework employs the [Khwaja and Mian (2008)](Khwaja and Mian (2008)) (KM) technique, which has by now been widely applied in many papers to identify credit supply effects at the loan (bank-firm) level.
Figure 2.5: Small versus Large Banks – coefficient plots
Note: These figures plot the estimated $\delta_t$ coefficients of equation 2.2 for small and large banks with 95% confidence intervals around them. Time is measured on a quarterly level and the vertical vermilion (dot-dashed), light-blue (dashed) and turquoise (long-dashed) lines mark the QE1, QE2 and QE3 episodes, respectively.
The sample consists of American non-financial firms that receive a loan to finance the firm’s operations. To quantify the effect of the QE shock on firm borrowing, the methodology compares the last loan received by the firm before QE with the first loan received after QE. Dealscan has information on the total dollar amount of each loan for the entire syndicate of lenders, and the size of the loan of each separate lender is recovered via their loan shares. These loan shares are computed following the imputation method introduced in Chodorow-Reich (2014b). For robustness, we also study the effect of QE on a “loan renewal” dummy, equal to 1 if the firm borrows again from a given lender after QE. This second measure of lending is robust to potential measurement errors in the dollar amount of lending.

Starting with the bank-firm level analysis and focusing on the sample of borrowers that obtained a loan in the pre-QE period can help address whether unobserved characteristics of borrowers, especially demand shocks, correlate at the lender level. The exercise begins by asking whether banks that increased overall C&I lending by more than other lenders also experienced a relative increase in their lending to the same firm when compared with other banks. Table 2.7 implements this test for each wave of QE by regressing the change in lending in a firm-bank pair on the QE exposure indicator and a full set of firm fixed effects that absorb any borrower characteristics which could influence loan outcomes. The inclusion of borrower fixed-effects necessitates every borrower to have more than one lender. As a result, the sample includes one observation for each lead lender and participant in the pre-QE syndicate. The following model is estimated:

\[
\log \left( 1 + L^{b,f}_{\text{post-QE}} \right) - \log \left( L^{b,f}_{\text{pre-QE}} \right) = \eta_f + \rho \cdot \text{Treat}_{b} + \nu_{b,f} \tag{2.3}
\]

---

19 The purpose of the loan is recorded in Dealscan as either “working capital” or “corporate purposes”.
20 For QE1, the pre-QE period spans September 2005 to November 2008, and the post-QE1 period covers December 2008 to January 2010. For QE2, the pre-QE2 timeframe spans September 2008 to November 2010, and the post-QE2 period goes from December 2010 to January 2012. For QE3, the pre-QE window spans July 2010 to September 2012, while the post-QE period encompasses October 2012 to December 2013. Choosing the two closest loans in each interval minimizes having overlapping intervals, a necessity to achieve sufficient sample size.
Table 2.7: Khwaja-Mian Estimator

<table>
<thead>
<tr>
<th></th>
<th>QE1</th>
<th>QE2</th>
<th>QE3</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>No. of firms</td>
<td>367</td>
<td>367</td>
<td>514</td>
</tr>
<tr>
<td>Observations</td>
<td>1384</td>
<td>1384</td>
<td>1763</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.01</td>
<td>0.01</td>
<td>0.00</td>
</tr>
</tbody>
</table>

**Note:** This table presents coefficient estimates from specifications at the C&I loan-level relating changes in lending to a bank’s MBS holding, for each wave of QE. The dependent variable is either i) the log change in the dollar amount of lending by a syndicate member from the pre- to the post-QE period (odd columns), or ii) a loan renewal dummy (even columns). Pre- and post-QE periods are defined as follows for each waves: QE1 (Sept. 2005 – Nov. 2008 and Dec. 2008 – Jan. 2010), QE2 (Sept. 2008 – Nov. 2010 and Dec. 2010 – Jan. 2012), QE3 (Jul. 2010 – Sept. 2012 and Oct. 2012 – Dec. 2013). Firm fixed-effects are included in columns (1)–(6), and $Treat_b$ denotes the MBS treatment indicator, splitting the sample according to median MBS holdings. The sample includes one observation for each lead lender and participant in the pre-QE syndicate. Standard errors are in brackets. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

where the dependent variable is the log change in the dollar value of lending by a syndicate member from the pre- to the post-QE period. $L_{t}^{b,f}$ is the dollar value of a loan multiplied by bank $b$’s imputed share of the loan to firm $f$ in period $t \in \{pre-QE, post-QE\}$, $\eta_f$ are firm fixed-effects, $Treat_b$ denotes the MBS treatment indicator, and $\nu_{b,f}$ is an idiosyncratic error term.

Across multiple specifications, we find similar results to the previous section. The treatment effect of QE1 and QE3 is positive and significant, while QE2 has virtually no effect. For instance, looking at column (1) of Table 2.7, one can see that while overall C&I lending contracted substantially after QE1, banks with MBS holdings above the median expanded their
lending by around 1.5% relative to the control group, *keeping the borrower fixed*. Columns (2), (4) and (6) show these results to also hold when using the loan renewal dummy as an outcome variable.

Even though C&I lending accounts for a relatively small portion of total bank credit, this firm-level evidence suggests the bank-level effect of QE documented in the previous section is not due to differential shocks to borrower quality or demand that are synchronous with the interventions.

### 2.5.4 Placebo Tests

The analysis throughout this paper has addressed the concern of non-random allocation of MBS by controlling for pertinent observable differences across banks and allowing for a heterogeneous response to the Fed’s large-scale asset purchases. This section goes one step further and presents evidence against yet another alternative hypothesis: that commercial banks with relatively large MBS-holdings expand their lending more aggressively during economic recoveries. This might be particularly relevant to the period around QE3, when the US economy was clearly gaining momentum. It is important to rule out that the patterns unveiled in the above figures and regressions were driven by a heterogeneous reaction among banks to the macroeconomic upturn.

To address this issue, the next placebo tests apply the same exact experiment as in section 2.5.2 but with a sample running from 2001 through 2004 using quarterly data. Shortly after the NASDAQ crash and following the collapse of the dot-com bubble, the US was in a recession during most of 2001, with the official ending date being 2001Q4. This allows to use 2002Q1 as a placebo LSAP date to investigate what happens to subsequent lending for the high and low MBS-holding groups of banks. Applying the same matching procedure, re-defining the $Treat_i$ indicator as equal to 1 if a bank belongs to the upper quartile of the MBS-to-Assets distribution in 2001Q1, and estimating specification 2.2 with all the
relevant control variables yields the coefficient plots for the main parameters of interest, $\delta_t$, in Figure 2.6.

Panels (a)–(c) of Figure 2.6 reveal there was no differential effect on either total, real estate, or C&I lending during the macroeconomic upswing following 2001. These placebo tests allow to go a long way in ruling out omitted variable biases pertaining to aggregate factors, and they are consistent with the main interpretation of the findings presented before. There is no evidence to suggest that any of the main results are simply picking up differences in how high MBS-holding banks structure their lending throughout the cycle. Rather, all of the effects seem to be driven by varying exposure towards the Fed’s intervention among lending institutions.

2.6 Mechanisms

This section explores the channels behind the effects of QE on bank lending documented in the previous section. Broadly speaking, large-scale asset purchases by the Fed can stimulate lending via balance sheet improvements at banks holding the particular assets being targeted.

The first channel by which QE can improve balance sheets is the “net worth channel”. When asset purchases have a large impact on security prices, the policy increases the value of bank security holdings, in turn increasing the mark-to-market value of bank equity. And given that commercial banks target constant leverage ratios (Adrian and Shin (2010b)), this increase in net worth would induce banks to expand their lending and take on additional debt. This mechanism has also been labeled “stealth recapitalization” by Brunnermeier and Sannikov (2014).

21 Leaving the treatment indicator unchanged at the 2008Q1 classification yields almost identical results as, in fact, there is an 84% overlap between banks considered as belonging to the treatment group at both points in time using the upper quartile definition. This is hardly surprising given how sticky the treatment allocations are found to be in Table 2.3.

22 Alternatively, one could have started by just looking at the evolution of relative lending-to-assets for both treated and control banks around the relevant period in 2001–2004, as in Figure 3.4. These plots end up showing very similar results, with relative lending-to-assets actually declining slightly for treated banks as opposed to the control group. For brevity, only the regression results are presented here.
Figure 2.6: **Placebo tests – coefficient plots**

Note: These figures plot the estimated $\delta_t$ coefficients of equation 2.2 with 95% confidence intervals around them for the period from 2001Q2 to 2004Q4. Time is measured on a quarterly level and the vertical vermilion dashed line marks the beginning of the post-2001 economic boom.
Figure 2.7: **Mechanisms: Net Worth**

Note: This figure displays the average growth of bank net worth around QE1 (between vertical vermillion dash-dotted lines), QE2 (between light-blue dashed lines) and QE3 (right of turquoise vertical long-dashed line). Banks in the treatment group belong to the upper quartile of the MBS-to-Assets distribution in 2008Q1, while banks in the control group belong to the lower quartile.

The data seems to support the idea of this net worth channel being at play during QE1, but not during the following waves of QE. Figure 2.7 displays the growth of bank net worth (mark-to-market equity) for the treatment and control groups over the entire period under consideration. The figure shows a striking increase in the net worth of banks holding relatively more MBS following QE1. On the other hand, there is virtually no difference between the two groups around both QE2 and QE3.

Why is the net worth channel restricted to QE1? While the implementation of QE1 led to a significant jump in the value of MBS, both QE2 and QE3 had a much more muted effect.
on these prices. Moreover, any price effect on Treasuries from QE2 is unlikely to lead to significant balance sheet improvement, as Treasuries holdings are such a small fraction of banking assets.

Two other pieces of evidence lend additional support to the net worth channel being uniquely associated with QE1. Firstly, only QE1 was linked to an expansion of the treated banks’ balance sheet. A necessary condition for the net worth channel to be at play is an increase in total assets following a rise in the value of securities. To empirically test this prediction, Table 2.8 presents results for difference-in-differences regressions that are identical to the pooled equations in the previous section, except for new dependent variables that are relevant to the mechanisms. Columns (1) and (2) display the results for the natural logarithm of assets as the dependent variable using both the discrete and continuous treatment allocations, where the coefficients for the continuous measure are standardized for ease of interpretation. Strikingly, the treatment effects are positive and highly significant for QE1, and insignificant for the other two waves.

The second piece of evidence relates to gains on securities. The net worth channel operates by increasing the value of securities holdings, independently of whether these securities are actually sold (realized gains) or kept on the books (unrealized gains). Figure 2.8 plots the effect of QE1 and QE3 on these gains (or losses) for the treatment and control groups. Panels (a) and (b) show that following QE1, the treated group experienced a significant relative increase in its gains on securities, both realized and unrealized. However, panels (c) and (d) reveal that no such differences exist after QE3. Columns (3) and (4) of Table 2.8 robustly confirm this finding in a pooled regression framework across all three waves of QE. The large,

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Note this observation is different from asking what would have been the counterfactual price absent the intervention. To detect the mechanism empirically, there must have been an actual price change.

Note: whenever \( \log(\text{Assets}_{it}) \) is used as the outcome variable, one of the regressors is taken to be \( \log(\text{Assets}_{i2008Q1}) \) interacted with the relevant QE indicator. All other controls remain unaltered.

Moreover, somewhere around the announcement of tapering in early 2013, when all MBS prices collapsed precipitously, both groups of banks seem to record some unrealized losses on their MBS holdings. In analogous but unreported graphs for QE2 we find absolutely no signs of a differential impact on realized or unrealized gains for the treatment and control groups. Again, this is consistent with QE working through a narrow channel and only affecting the particular assets being targeted. Since commercial bank holding companies hold very little Treasuries, the absence of any notable effects is not surprising.
<table>
<thead>
<tr>
<th></th>
<th>log($\text{Assets}_{it}$)</th>
<th>log($\text{Currency}_{it}$)</th>
<th>log($\text{RGains}_{it}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>$Treat_{M,i} \cdot QE_1$</td>
<td>0.025***</td>
<td>-0.041</td>
<td>0.635***</td>
</tr>
<tr>
<td></td>
<td>[0.009]</td>
<td>[0.030]</td>
<td>[0.185]</td>
</tr>
<tr>
<td>$Treat_{T,i} \cdot QE_2$</td>
<td>0.016</td>
<td>0.013</td>
<td>-0.036</td>
</tr>
<tr>
<td></td>
<td>[0.013]</td>
<td>[0.035]</td>
<td>[0.119]</td>
</tr>
<tr>
<td>$Treat_{M,i} \cdot QE_3$</td>
<td>0.006</td>
<td>0.048*</td>
<td>-0.033</td>
</tr>
<tr>
<td></td>
<td>[0.010]</td>
<td>[0.026]</td>
<td>[0.105]</td>
</tr>
<tr>
<td>$(MBS_{Asset})_{i} \cdot QE_1$</td>
<td>0.007**</td>
<td>-0.006</td>
<td>0.180***</td>
</tr>
<tr>
<td></td>
<td>[0.003]</td>
<td>[0.010]</td>
<td>[0.043]</td>
</tr>
<tr>
<td>$(TRE_{Asset})_{i} \cdot QE_2$</td>
<td>0.000</td>
<td>-0.005</td>
<td>-0.044</td>
</tr>
<tr>
<td></td>
<td>[0.003]</td>
<td>[0.006]</td>
<td>[0.061]</td>
</tr>
<tr>
<td>$(MBS_{Asset})_{i} \cdot QE_3$</td>
<td>0.001</td>
<td>0.008*</td>
<td>-0.026</td>
</tr>
<tr>
<td></td>
<td>[0.002]</td>
<td>[0.004]</td>
<td>[0.020]</td>
</tr>
<tr>
<td>$QE_t$</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Controls $\cdot QE_t$</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Bank FEs</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of banks</td>
<td>1,939</td>
<td>3,949</td>
<td>1,939</td>
</tr>
<tr>
<td>Observations</td>
<td>59,870</td>
<td>128,970</td>
<td>59,844</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.439</td>
<td>0.372</td>
<td>0.104</td>
</tr>
<tr>
<td>$p$-value</td>
<td>0.0500</td>
<td>0.0131</td>
<td>0.0223</td>
</tr>
</tbody>
</table>

Note: This table presents coefficient estimates from specifications at the BHC level relating lending from 2008Q1 to 2014Q4 with banks’ initial exposure towards LSAPs, as captured by their treatment group membership or standardized MBS-to-Assets ratio back in 2008Q1. The reported $p$-value tests for coefficient inequality between $QE_1$ and $QE_3$. Standard errors [in brackets] are clustered at the bank-level to allow for serial correlation across time. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

Positive and significant coefficients in the first and fourth rows suggest that the net worth channel was unique to $QE_1$.

The channel behind the increase in lending following $QE_3$ is different. Another way by which $QE$ can improve balance sheets is through increasing bank liquidity via acquisitions of MBS directly from these banks, even without large price effects. More precisely, such a
Figure 2.8: Mechanisms: Realized and Unrealized Gains
Note: Panels (a) and (b) display the average net realized and unrealized gains (or losses) on securities as a fraction of equity around QE1 (red vertical line), respectively. Panels (c) and (d) plot the corresponding figures around QE3. Banks in the treatment group belong to the upper quartile of the MBS-to-Assets distribution in 2008Q1, while banks in the control group belong to the lower quartile.
“liquidity channel” works through a reallocation on the asset side of banks’ balance sheets. As MBS become more liquid, banks can swap them for reserves and expand lending while keeping their total assets fixed. The additional balance sheet illiquidity coming from more lending is mitigated by the extra liquidity on the rest of the asset side. The key difference between this channel and more traditional transmission mechanisms is that balance sheets do not expand, and the increase in lending occurs through a reallocation on the asset side.

The results in Table 2.8 support this interpretation. Columns (2) and (3) show a positive and significant treatment effect on non-interest bearing reserves after QE3, but not following the previous large-scale asset purchase rounds. In other words, treated banks experience an increase in cash relative to the control group only after QE3. Together with the absence of a relative asset expansion or any substantial gains on securities, this evidence is indicative of QE3 operating through a liquidity mechanism as opposed to a net worth channel. On the other hand, the liquidity channel is unlikely to exist for QE2 as Treasuries are extremely liquid even in the absence of any interventions by the Fed, a notion reinforced by the results in Table 2.8.

The key message of this section is that large-scale asset purchases can stimulate bank lending through more than one channel. In particular, although QE1 and QE3 had roughly similar effects on bank lending, they operated through vastly different mechanisms that depended on the joint response of security prices and market conditions. Future work could make use of higher frequency data to shed more light on how overall liquidity created by QE is subsequently used and spread through the banking sector.

2.7 Conclusion

This paper started out by documenting large cross-sectional heterogeneities in commercial banks’ mortgage-backed securities holdings and their relative exposure to large-scale asset

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26In principle, this channel can also be at play during QE1. The fact that we find no evidence for it can suggest that it was either dwarfed by the net worth channel, or that market conditions were too bad for banks to react very strongly to it.
purchases. The average MBS-to-Assets ratio is 8% and the standard deviation is about 10% in a sample that consists of quarterly data on US commercial banks from 2008Q1 until 2014Q1, aggregated to the bank holding company level but excluding any non-bank subsidiaries.

The analysis shows that banks with a relatively large fraction of MBS on their balance sheet expand lending more aggressively after QE1 and QE3 when the Fed targeted those particular types of securities. Within-firm loan-level regressions further demonstrate that the results are not driven by any simultaneous demand-side shocks. The channels tend to vary depending on the magnitude of the price impact following each intervention, with substantial evidence pointing toward a “net-worth channel” around QE1 and a “liquidity mechanism” after QE3.

Contrary to conventional wisdom, these results suggest that QE had a differential effect on various types of financial institutions in the economy rather than “raising the tide and lifting all boats” for everyone equally via general equilibrium effects. Hence the distribution of MBS holdings across agents is crucial to the understanding of the re-distributive effects and the exact transmission mechanisms of unconventional monetary policy. This paper is the first to provide direct empirical support for the importance of targeting specific assets rather than just quantity during any large-scale asset purchasing.
Appendix

Banks are indexed with $i$, whereas $t$ stands for the quarter. All mortgage-backed securities price series are sourced from Bloomberg. All bank-level variables are drawn from the Consolidated Reports of Condition and Income (FFIEC 031 and FFIEC 041 files). Note that flow variables taken from the income statement of the Call Reports are reported each quarter as “year-to-date”. To transform a year-to-date variable into a quarterly one, the variable is taken as listed for the first quarter of each year, and for each subsequent quarter, $Q = \{2, 3, 4\}$, the variable is calculated as the difference between the year-to-date values between $Q$ and $Q - 1$.

- $\left( \frac{\text{MBS}}{\text{Asset}} \right)_{i,t}$: \[\text{[held-to-maturity amortized cost mortgage-backed securities + available-for-sale fair value mortgage-backed securities]}/\text{Assets}_{i,t}\]

- $\left( \frac{\text{TRE}}{\text{Asset}} \right)_{i,t}$: \[\text{[held-to-maturity amortized cost US Treasuries + available-for-sale fair value US Treasuries]}/\text{Assets}_{i,t}\]

- $\text{Size}_{i,t}$: $\log(\text{Assets}_{i,t})$, where Assets = $\text{RCFD2170}$ for banks with foreign offices; = $\text{RCON2170}$ for banks w/o foreign offices.

- $\text{Equity}_{i,t}$: $1 - \text{Liabilities}/\text{Assets}$, where Liabilities = $\text{RCFD2948}$ and Assets = $\text{RCFD2170}$ for banks with foreign offices, and = $\text{RCON2948}$ and = $\text{RCON2170}$ for banks w/o foreign offices.
• **Lending}_{i,t}: loans and leases, net of unearned income = \text{RCFD2122} for banks with foreign offices, and = \text{RCON2122} for banks w/o foreign offices.

• **RE Lending}_{i,t}: loans secured by real estate = \text{RCFD1410} for banks with foreign offices, and sum of \text{RCONF158}, \text{RCONF159}, \text{RCON1420}, \text{RCON1797}, \text{RCON5367}, \text{RCONF5368}, \text{RCON1460}, \text{RCONF160}, \text{RCONF161} for banks w/o foreign offices.

• **C&I Lending}_{i,t}: commercial loans = sum of \text{RCFD1763} and \text{RCFD1764} for banks with foreign offices, and \text{RCON1766} for banks w/o foreign offices.

• **Reserves}_{i,t}: cash and balances due from depository institutions = sum of \text{RCFD0081} and \text{RCFD0071} for banks with foreign offices, and sum of \text{RCON0081} and \text{RCON0071} for banks w/o foreign offices.

• **Currency}_{i,t}: non-interest-bearing balances and currency and coin = \text{RCFD0081} for banks with foreign offices, and = \text{RCON0081} for banks w/o foreign offices.

• **Net Income}_{i,t}: net income (loss) attributable to bank = \text{RIAD4340}. This variable has to be converted from year-to-date to quarterly as explained above.

• **ROA}_{i,t}: = Net Income}_{i,t} / Assets}_{i,t}

• **Realised Gains}_{i,t}: realized gains (losses) on held-to-maturity securities [\text{RIAD3521}] + realized gains (losses) on available-for-sale securities [\text{RIAD3196}]. NB: \text{RIAD3521} and \text{RIAD3196} are transformed from year-to-date to quarterly as explained above.

• **Unrealised Gains}_{i,t}: net unrealized gains (losses) on available-for-sale securities, = \text{RCFD8434} for banks w. foreign offices; = \text{RCON8434} for banks w/o.

• **Gap}_{i,t}: duration gap = average repricing/maturity gap between a bank’s assets and liabilities at the end of quarter \text{Q}. 

109
2.A Bibliography


Chapter 3

Endogenous Quality and Exchange Rate Pass-Through

This chapter is co-authored with Daniel Goetz.

3.1 Introduction

A large body of empirical work documents a small response of traded good price indices to exchange rate fluctuations. These facts are usually described by saying that exchange rate pass-through is slow and incomplete. Surprisingly, very large devaluations are similarly associated with declines in the real exchange rate and correspondingly low inflation rates. In this paper, we use a uniquely granular micro-dataset spanning Russia’s huge devaluation episode in late 2014 to argue that compositional shifts in product offerings are a pertinent force inducing seemingly low price levels after a cost shock.

Basic international macro and trade models with firm heterogeneity predict low aggregate price level changes due to compositional shifts in traded goods. During a devaluation, as costs rise foreign firms that are least efficient—those with the highest marginal costs—no longer find it profitable to trade. The rise in the local price index is therefore dampened by the exit of high cost, high price goods. We document in the data that there is indeed
a reallocation towards relatively low cost goods after a currency devaluation. However, we further show that there is a reallocation towards relatively low quality goods as well. We view this as a puzzle: if a cost shock precipitated by an exchange rate movement induces the least efficient foreign firms to exit, why is there a reallocation towards lower quality goods? Moreover, how does this quality reallocation interact with the cost reallocation to affect inflation and consumer welfare?

We address these questions by constructing a structural model of demand and firm entry and exit, where consumers value both low prices and high quality. Unlike in models built with constant elasticity of substitution utility, marginal cost and quality will not be isomorphic for firm pricing in this model. Therefore, goods in the model truly vary on two dimensions. We make the intuitive argument that if the joint distribution of marginal cost and quality has a positive covariance, then quality downgrading can be rationalized as high cost, high quality firms drop out. Although high quality has an insulating effect for high cost firms, if the \textit{ex ante} variance of costs is high relative to quality then a proportional cost-shock will nonetheless induce these firms to exit in greater numbers than low cost firms.

Using a calibrated version of the model, we find that a proportional cost-shock equal in magnitude to the Russian ruble devaluation in 2014 leads to a substantial reallocation towards low cost, low quality goods. The lowest quartile of the cost distribution increases its relative share of firms 10 percent respectively after the cost shock, while high cost quartiles reduce their shares by between 17 and 43 percent. Because of a positive empirical covariance between quality and costs this also represents a reallocation towards lower quality goods. By way of comparison, in a model that only features cost heterogeneity the lowest quartile increases its share by only 6 percent. This results from a subtle feature of including quality heterogeneity: forcing high quality firms to exit reduces the average markup by making the environment more competitive even in the absence of a cost shock. This especially affects medium cost, medium quality firms, leading more of these firms to exit than in the case with only cost heterogeneity.
Including the quality dimension also affects how consumer welfare changes after the depreciation. In the model with quality heterogeneity, welfare decreases by 21 percent in response to the shock. In contrast, in the model with only cost heterogeneity, the welfare decrease is only 14 percent. Relative to the 50 percent cost shock we impose these welfare reductions may seem modest; that the reduction is not higher reflects both a decrease in markups across the board as well as consumer willingness to substitute to domestic goods which do not experience a cost shock.

For our mechanism, we considered the Russian ruble devaluation purely as a cost shock. There may be some worry that the reallocation towards lower quality goods stems from household substitution due to a corresponding real income shock. This phenomenon has been called the “flight from quality”, and has been observed in the aftermath of large contractionary devaluations (Burstein et al. [2005]), potentially contaminating the measurement of CPI. We present several pieces of evidence that for the online retailer under consideration, the consumer response to the exchange rate shock was negligible in the short run. Firstly, since we observe both inventories and sales, we show that inventory reallocates towards low cost and low quality goods and that this is not driven by mass purchases of expensive items in an effort to move consumption forward. Firm choices, rather than consumer behavior, drives the reallocation towards low cost goods.\footnote{Several other industries are likely to have been affected by the same quality downgrading mechanism during the course of the Russian currency crisis. In particular, a study by PwC found that domestic food producers reacted to the economic collapse by offering new and cheaper products, economizing on packaging, as well as switching to lower quality ingredients when manufacturing their produce. Source: “Food is changing in taste and weight.”, Vedomosti, July 19, 2015.} Secondly, we find in a robust difference-in-differences analysis that regions in Russia whose economies were heterogeneously exposed to the devaluation experienced no differential change in demand patterns. Thirdly, the Russian apparel market data used in this paper is an ideal laboratory to study how textile fabrics, which can be seen as a direct proxy of quality, change following large cost shocks. Restricting attention to one category of goods, shirts, we find that high quality materials disappear entirely from the composition during the first post-devaluation season.
We take care to show that although our data is from an online retailer, it exhibits similar features to data used in other studies of currency devaluations. In this way we hope to convince the reader that there is nothing “unusual” about the devaluation transmission mechanism we observe, and therefore that the results are externally valid. In particular, we document a relatively subdued aggregate price reaction across the store, and show it mainly to be the result of the low frequency of price changes, with only 8% of all goods being re-priced each month. Conditional on price adjustments, however, we find that exchange rate pass-through is almost immediate and complete for imported clothing items. Both of these features of the data are present in studies using offline sales, which we discuss below.

### 3.1.1 Relation to the Literature

This paper is closely related to studies that have focused on large exchange rate devaluations and pass-through into prices, relying on aggregate industry level data ([Burstein et al. (2005)](#), [Goldberg and Campa (2010)](#)) as well as micro studies using product-level prices: [Broda and Weinstein (2008)](#) examine retail price data for individual products (UPCs) across different retail establishments, [Gopinath et al. (2011)](#) use data from a single retail chain to decompose variation in prices across the US and Canada into costs and markups. [Burstein and Jaimovich (2012)](#) use the same data to analyze patterns of wholesale prices to shed light on pricing-to-market (PMT) in aggregate and micro-level real exchange rate movements. [Fitzgerald and Haller (2014)](#) also provide very direct evidence on PMT by comparing the exchange rate response of prices of the same item sold to both the domestic and the international market. The lack of data on domestic product prices at the firm-level matched with international data shifted the focus of analysis from the response of domestic prices broadly to the response of prices of exporters and importers. For example, [Gopinath and Itskohki (2010)](#) provide indirect evidence that is consistent with the presence of strategic complementarities in pricing. [Amiti et al. (2014)](#) decompose the variation across exporters in the exchange rates pass-through into markup and marginal cost channels, while [Amiti
et al. (2016) extend the analysis to provide direct evidence on strategic complementarities in price setting across industries. Recently, Cravino and Levchenko (2016) have looked into the distributional consequences of large devaluations and showed the cost of the consumption basket of people in the bottom decile of the income distribution to rise a lot more than of individuals in the first decile.

The paper also builds on the literature estimating pass-through and markup variability in specific industries such as cars (Feenstra et al. (1996)), coffee (Nakamura and Zerom (2010)), and beer (Goldberg and Hellerstein (2013)). These industry studies typically rely on structural estimation by adopting a specific model of demand and market structure, which is tailored to the industry in question. We take a similar approach by considering a framework that is similar in spirit to most dynamic oligopoly models in the applied IO literature, starting with Ericson and Pakes (1995). In notation and exposition we closely follow Weintraub et al. (2008). When estimating the model, we take the Bajari et al. (2007) methodology one step further by using it in a simulated method of moments approach to estimate parameters. Following Khandelwal (2010), we also exploit both price and quantity information to estimate the quality of products offered by the online store over time.

This study is also linked to a body of existing work quantifying how the treatment of sales influences measured degrees of price rigidity in posted prices. Bils and Klenow (2004), Eichenbaum et al. (2011), and Kehoe and Midrigan (2015) provide evidence on the extent to which discount prices influence effective prices paid by households in reality. Coibion et al. (2015) build on this literature by investigating the cyclicality in both posted retail and effective prices actually paid by consumers. Rather than discount sales, the authors find that consumer expenditure reallocation across stores in response to economic conditions drives a wedge between cyclical changes in posted and effective prices. Our key results are complementary to these findings as they document a separate amplification channel on the part of firms wishing to adjust the quality (and cost) of their products in response to aggregate economic shocks.
The focus of our paper is not on the pass-through of cost shocks at the good level, however a number of important factors explaining incomplete exchange rate pass-through have been studied over the past decades. Firstly, short-run nominal rigidities with sticky local currency prices (LCP) lead to zero pass-through for firms that do not respond to cost shocks immediately \( \text{Devereux and Engel (2002), Gopinath and Rigobon (2008)} \). Secondly, pricing-to-market (PTM) arises in a framework with variable markups where firms choose different prices for various destination markets depending on local conditions. \( \text{Atkeson and Burstein (2008)} \) provide a quantitative exploration of the PTM channel and its implication for aggregate prices. And thirdly, local costs may play a key role in determining pass-through by driving a wedge between prices and import costs and lowering firms’ responsiveness to exchange rate fluctuations \( \text{Burstein et al. (2003) and Goldberg and Campal (2010)} \).

Finally, the paper is related to a number of studies on “flight from quality” and international trade. In a recent contribution, \( \text{Medina (2016)} \) shows that both quality upgrades and increases in export activity can be direct outcomes of import competition, quantifying the importance of both factors. \( \text{Chen and Juvenal (2015)} \) show that higher quality goods enjoyed a stronger growth in exports before the crisis, but this trend reversed during the Great Recession, largely due to income shocks. \( \text{Chen and Juvenal (2016)} \) develop a model with more pricing-to-market and a smaller response of export volumes to a real depreciation for higher quality products, while \( \text{Bems and Di Giovanni (2015)} \) show that income effects can drive expenditure switching between domestic and imported goods using Latvian scanner-level data during the 2008 crisis. In contrast to these papers, we uncover a novel endogenous amplification channel on the firm side driving quality adjustments in product offerings.

The paper proceeds as follows. Section 3.2 provides an overview of the data and institutional background used in the paper. Section 3.3 presents stylized facts about price adjustments, potential demand (substitution and income) channels, as well as direct evidence on quality downgrading in the Russian online apparel industry. Section 3.4 describes the demand model. Section 3.5 outlines the estimation procedure. Section 3.6 explains how
each moment from the data is obtained. Section 3.7 presents results and counterfactual simulations. Section 3.8 concludes.

3.2 Data

3.2.1 Data Sources

The main data is sourced from one of two most prominent online apparel marketplaces and distributors in Russia. The store specializes in clothing but offers certain semi-durable products as well. The company is a subsidiary of a publicly traded German enterprise, listed on the Frankfurt Stock Exchange. The data are available at daily frequencies and the main period of analysis is from January 1, 2012 until September 18, 2015. As of today, the online retailer operates in four Commonwealth of Independent States (CIS) countries (Belarus, Kazakhstan, Russia, and Ukraine), although the present study focuses exclusively on the largest market, which is Russia.

The following set of variables are available at a stock keeping unit (SKU) level, sorted by orders over time: article id, SKU, product characteristics (such as size, color, fabric composition, premium status, brand, date of introduction, season, gender, target group or category etc.), order time and date, shipping method, city and region of the order, regular retail and discount prices, average wholesale costs, customer id, customer OS, inventory count on an almost daily level, and invoice currencies. This structure of the data allows to extract the precise number of quantities ordered and sold across thousands of destination cities within Russia—a central advantage relative to extant studies with no observations on the quantity dimension.

We further merge this dataset with aggregate macro and regional variables, such as the EURRUB and USDRUB exchange rates, regional GDP growth in 2015, as well as regional unemployment and income levels that are sourced from Global Financial Data and Russian Federal State Statistical Service Agency, respectively.
3.2.2 Institutional Background

Before the main analysis, it is important to highlight some key institutional features of the e-commerce apparel market in Russia as well as the huge devaluation episode in late 2014. Starting with the latter, the Russian currency crisis of 2014 broadly refers to a major decline in confidence that caused investors to sell off their Russian assets and led to a fall in the value of the Russian ruble. The lack of confidence in the Russian economy stemmed from two major sources: first and foremost, the price of crude oil, a key export of Russia, declined by nearly 50% between its yearly high in June 2014 and December 2014. The second factor was related to international economic sanctions imposed on Russia following the annexation of Crimea and a military intervention in Ukraine.\footnote{It should be noted that Russian counter-sanctions against the EU were targeted exclusively at the food and agricultural sector and had no direct effects on apparel imports from South-East Asia.} As shown in Figure 3.3, part of the results were a ruble depreciation of about 60% against the US dollar between July and December 2014.

[Insert Figures 3.2 and 3.3 here]

From the vantage point of an individual firm, these abrupt exchange movements represent exogenous cost shocks to the values of imported inputs or consumer products. We later use this variation together with invoice currency information at the SKU-level to instrument for prices when estimating demand. As far as the apparel industry is concerned, its most distinctive trademark feature pertains to seasonality: most of the goods in our sample have a very short lifespan (the median is 182 days) and are put on sale as soon as their native season ends. Figure 3.2 provides a depiction of the percentage revenues attributable to each season over time. And since, by definition, any given SKU remains perpetually assigned to the same season, it is clear that hardly any goods live beyond three quarters of a year. Product-level entry and exit margins of adjustments will therefore be the central mechanism by which quality changes might come about. This industry structure necessitates brands to come up with novel products on a half-yearly basis, while strongly negative economic perturbations
will influence the types of goods each firm chooses to supply. Yet since most apparel manu-
ufactures aim to retain their customer loyalty, the bulk of any quality downgrading should
be expected to occur across rather than within brands over time.

A very first glance at the data manages to reveal a number of striking regularities sup-
portive of potential compositional shifts in product offerings. Figure 3.3 shows that the
steep ruble depreciation at the end of 2014 led to a notable increase in the deseasonalized
average wholesale cost of goods sold (mean COGs). However, one can also discern a fall in
the deseasonalized average inventory-weighted wholesale cost (i-weighted mean COGs) over
the same time frame. This pattern is not driven by a large scale removal of high cost goods
from the retailer’s warehouses (which could perhaps be rationalized with consumers mov-
ing forward consumption), but rather by a disproportionate amount of stocking-up on low
cost goods: the closely associated movement of the deseasonalized average quantity-weighted
wholesale cost (q-weighted mean COGs) confirms this interpretation. In fact, it is worth
pointing out that simple mean wholesale costs are consistently below both quantity- and
inventory-weighted mean wholesale costs until the onset of the currency crisis in late 2014,
when the order is reversed and the simple mean reaches its maximum level.

3.3 Empirical Motivation

We have three objectives in this section: first, we present direct evidence on quality down-
grading by looking at the composition of textile fabrics within a narrow category of goods
(shirts). Second, we justify our exclusive focus on the devaluation as a cost shock by show-
ing that demand effects of the shock were negligible. Finally, we provide evidence that the
pattern of price adjustment for our data is not unusual. The concern that conclusions de-

erived from the pricing behavior of an online retailer might not be externally valid must be

addressed, as the literature has found that mechanisms that are not present online—such as
menu costs—are important for pass-through. We show that both the price index of goods
sold by the firm as well as the pattern and frequency of individual goods price adjustments are not unusual.

3.3.1 Quality

Due to the highly seasonal nature of the apparel industry, and independent of within-SKU pass-through, a large chunk of the response to the currency crisis and resulting cost shock could naturally have occurred on the extensive margin of goods entry and exit. The objective of this section is therefore to construct a quality index for products in the shirts category offered by the online store using a similar approach as the one employed by the BLS in calculating the CPI.

Initially, quality weights have to be constructed for each fabric type. We choose to base these weights on relative textile prices from China, the main production country for almost every apparel item in the dataset. Further, the vast majority of all fabrics happen to be either cotton, viscose or polyester fibers, and are ranked according to the highly stable relative cost difference of these materials over time. Once these time-invariant fabric rankings are obtained, each product can be assigned a quality measure, \( \lambda_{i,t} = \sum_k \omega_k \cdot \lambda_{i,k,t} \), for each season \( t \), SKU \( i \), fabric type \( k \) and its respective quality ranking \( \omega_k \). The cross-seasonal quality index is then computed as follows:

\[
Q_t = Q_{t-1} \cdot \frac{\bar{\lambda}_t}{\bar{\lambda}_{t-1}}
\]

(3.1)

where \( Q_t \) is the quality index for season \( t \), \( Q_{SS2012} \) is normalized to 100, and \( \bar{\lambda}_t \) is the simple average SKU quality measure for season \( t \).

[Insert Figures 3.6 here]

Panel (a) of Figure 3.6 shows the available shirt sole material fabric composition over time, distinguishing between fall-winter (F) and spring-summer (S) seasons. Panel (b) plots the time-series for the quality index in equation 3.1, splitting goods by whether they are imported
or locally produced. The results show striking patterns: the more expensive higher quality materials disappear entirely from the composition during the first post-crisis season (15S). In particular, the percentage of natural leather and agriculturally grown gum fabrics abruptly drops to zero, leaving all existing shirts composed of the artificial and cheaper polyurethane material. Looking at the quality index, it is obvious that all of these adjustments are driven by imported goods rather than the locally produced items. And even though the quality index for Russian goods displays some volatility due to the much smaller fraction of apparel manufacturing in Russia, the quality of these products does not react in any noticeable way to the massive ruble devaluation while the fabrics based quality of imported shirts drops by around 30% relative to the previous spring-summer season.

Taken together these findings suggest a substantial compositional reallocation on the part of fashion manufacturers from higher towards lower quality goods.

### 3.3.2 Demand Channel

One might suspect the observed compositional changes stem from a large demand shift towards cheaper or lower quality goods as a result of an income shock to consumers, rather than a cost shock to apparel manufacturers. In this section we assess the quantitative importance of this mechanism by looking at regions that were more adversely affected during the crisis and comparing their demand patterns to regions that had higher economic growth. We find little evidence of demand non-homotheticities or consumption reallocation towards cheaper goods in Russian regions (oblasts) suffering from extremely low or even negative economic growth in 2015. The basic approach entails a difference-in-differences (DinD) estimation strategy of the following form:

\[
\log(Y_{it}) = \alpha_i + \sum_t \gamma_t D_t + \sum_t \delta_t (D_t \cdot \text{Growth}_i) + X_{it}^\prime \theta + \sum_t \psi_t (D_t \cdot X_{it}) + \epsilon_{it} \quad (3.2)
\]

\[
\forall i, \forall t \in \{2012m1, \ldots, 2015m9\} \setminus \{2014m12\}
\]
where \( Y_{it} \) is either the i) median regular price, ii) mean (weighted or unweighted by sales) regular price, or iii) fraction of premium sales in region \( i \) at time \( t \), \( \alpha_i \) are region fixed effects, \( \text{Growth}_i \) is the nominal regional GDP growth in 2015, \( D_t \) is an indicator for the time period (year-month), with 2014m12 taken as the omitted category, \( (D_t \cdot \text{Growth}_i) \) represents an interaction term between the time indicators and a region’s economic performance in 2015, and \( X_{it} \) is a matrix of control variables that includes total regional sales (in logs), as well as regional unemployment and income levels. All standard errors are clustered at the region-level to allow for serial correlation across time.

The Russian currency crisis had a vastly differential impact on various regions of the country. This provides for a clean distinction between exposed (low growth) and unexposed (high growth) oblasts that can be utilized when estimating specification 3.2. Panel (a) of Figure 3.7 shows a map with geographic regions that grew relatively fast (in dark colors) as well as slowly (in light colors) in 2015. Exclusively devoting attention to oblasts with positive retail sales, the steepest contraction saw regional GDP growth of \(-10.1\%\) while the oblast with the highest growth expanded by 16.1\%. The standard deviation of income growth was 3.26 over this period.

As would be necessary with any DinD estimation approach, this specification also provides evidence on the parallel trends assumption in all outcome variables. That is, in the absence of treatment the unobserved disparities between high- and low-growth regions should be constant over time – the validity of the estimation procedure relies on outcome variables that would have continued to develop as they did before the economic shock in all regions. Unless this assumption is valid, the estimated treatment effects would be biased versions of the true impact. As an additional robustness check on the identification strategy, all control variables are interacted with the \( D_t \) indicators to allow for possible heterogeneous responses to negative economic shocks across very distinct regions (e.g. poor vs. richer oblasts might react differently to the crisis).
The main parameters of interest are the $\delta_t$ since they capture the difference between crisis exposed and relatively unscathed regions over time. The estimated fixed-effects model includes leads going back to early 2012 and lags reaching the last available month, September 2015. The specification allows for any causal direction of the findings and assesses if the effects grow or fade over time.

One may also entertain a causal interpretation of the $\delta_t$ estimates in equation 3.2 for other important reasons. Firstly, about 93% of goods sold by the retailer are not produced in Russia, and even when the good is home made it is almost never manufactured in the region under consideration. Hence the specification will not suffer from endogeneity issues typically associated with regressions of prices on economic activity. For instance, unobserved productivity innovations for a specific SKU are unlikely to be correlated with local growth rates. In principle, aggregate shocks could lead to simultaneous movements in prices of goods and local economic growth. But since time fixed effects are included, they should eliminate this endogeneity issue too. Finally, the retailer does not discriminate in price setting across geographic regions within Russia and thus any observed divergence in regional (sales weighted) median or mean prices can only be explained by movements in quantities (purchases).

The findings are summarized in Figure 3.7, which plots the key estimated parameters of interest, $\hat{\delta}_t$, with 95% confidence intervals around them. As would be consistent with the parallel trends assumption, the estimates in Panel (b) show no robust differences between the positively exposed (high growth) and negatively hit (low growth) regions in the months prior to the onset of Russia’s currency crisis. Then, starting around mid-2014, volatility in the treatment effects for all three outcome variables starts to appear. However, the results are insignificant and hardly moving in the expected positive direction. Together with unreported but also highly robust evidence suggesting no differential effects on total regional sales, this leads us to conclude that income shocks across Russian geographies played a marginal role.
in the observed compositional shifts in the affordable fashion industry and that endogenous amplification channels on the firm-side must be driving most of the quality downgrading.

### 3.3.3 Prices

**Price Indexes**

The first objective is to construct a price index for the online store using a similar approach as the one employed by the BLS in calculating the CPI. Initially, the total quantity sold is computed for each good (SKU) in every month. The index is aggregated to the monthly level to reduce the number of missing values. The following category-level Laspeyres price index is used:

\[ P_{Lj,t} = \frac{\sum_{i \in j} p_{i,t} q_{i,t}}{\sum_{i \in j} p_{i,t-1} q_{i,t}} \]

where \( P_{Lj,t} \) is the Laspeyres price index for category \( j \) in month \( t \), \( P_{Lj,2013m1} \) is set to equal 100, the price of a specific good \( i \) at time \( t \) is given by \( p_{i,t} \), and \( q_{i,t} \) is the average monthly quantity sold of good \( i \) across months \( t-1 \) and \( t \). By fixing quantities in this way, household consumption patterns are held fixed as prices change. The basket of goods is updated in two-month intervals (e.g. Jan–Feb, Feb–March, etc.), and the resulting indexes are chained to produce one index for each category, denoted by \( P_{j,t} \).

A key issue when computing monthly price indexes is how to deal with missing values from period-to-period. For example, a product may show up in month \( m \) but not in month \( m + 1 \), making it impossible to compute the price change for that good between two months. Missing values may be due to new products entering the market, old products withdrawing from the market, and seasonality in sales. Given the highly ephemeral nature of products in the apparel industry, we build a month-to-month chained price index to ensure the presence
of a large enough fraction of goods at every step of the calculation. This way, more than 50% of SKUs are present in each period.

[Insert Figures 3.4 and 3.5 here]

The results for the aggregate price index based on all goods listed by the online marketplace reveal a striking pattern: Figure 3.4 suggest that as the ruble devalued by about 60% against the US dollar, the ruble prices of imported apparel items rose only by approximately 4%. Locally produced (Russian) goods faced a similar albeit somewhat smaller price inflation during this period. After about four months into 2015, prices appear to have stabilized at a new and slightly higher level.

Puzzling as they may seem, these low inflation numbers are mainly explained by the low frequency of price adjustment during the whole period of operations. Figure 3.5 shows the sales-weighted and unweighted percentages of goods that faced a price change in any given month relative to the previous month. The average percentage of price adjustments is roughly 8% throughout all years for which data is available. Price adjustments seem to become slightly more frequent just before each winter sale period, except for the currency crisis year of 2014 when there were fewer price decreases (discounts) than normally.

Besides explaining the limited reaction of aggregate price indexes, these pattern once again underscore the importance of the extensive margin of product entry and exit. In particular, all goods are put on sale in the latter half of their lifespan, and on average after 60% of the weeks a good is available for purchase have been passed. This mechanism of phasing out older generations of products before the arrival of new ones defines transitions between seasons in many industries.

Micro-dynamics of Price Adjustments

Once a conditioning on price adjustments is introduced, however, inflation and within-SKU pass-through become a lot higher, and turn out to be almost immediate and complete for imported goods.
At the SKU-level, we estimate pass-through into prices of exchange rate shocks realized during the most recent period of price non-adjustment and of those that were realized prior to the previous price adjustment. As discussed in the literature (Gopinath and Itskhoki (2010)), in the absence of real rigidities, all adjustment should take place at the first instance of price change and hence the coefficient on the exchange rate change prior to the previous price adjustment should be zero. More precisely, the following regression is estimated:

$$\Delta \bar{p}_{i,t} = \beta_1 \Delta \tau_1 e_t + \beta_2 \Delta \tau_2 e_{t-\tau_1} + \eta_i + \epsilon_{i,t}$$

(3.4)

where $i$ indexes the SKU, $t$ stands for the date, the outcome variable, $\Delta \bar{p}_{i,t}$, is the change in the log ruble price of a good, conditional on price adjustment, and $\Delta \tau_1 e_t \equiv e_t - e_{t-\tau_1}$ is the cumulative change in the log of the bilateral nominal exchange rate over the duration when the previous price was in effect (denoted as $\tau_1$). Analogously, $\tau_2$ denotes the duration of the previous price of the firm so that $\Delta \tau_2 e_{t-\tau_1} \equiv e_{t-\tau_1} - e_{t-\tau_1-\tau_2}$ is the cumulative exchange rate change over the previous period of non-adjustment, i.e. the period prior to the previous price change. Finally, solely within-SKU variation is exploited via the inclusion of good-specific fixed effects, $\eta_i$, and standard errors are clustered at the SKU-level to allow for serial correlation across time.

Table 3.4 reports the results from estimations of regression 3.4, with evidence for various sub-samples of the data and restricting attention to goods that generate above 90% of all revenues, i.e. with a lifespan of less than 300 days. In contrast to some findings in previous studies, exchange rate shocks that took place prior to the current period of non-adjustment have a much weaker and hardly robust effect on current price changes. This is reflected in the estimated $\beta_2$ coefficient being statistically indistinguishable from zero in across specifications.

When the regression model is restricted to imported goods only in columns (1) through (4), pass-through occurs immediately after the cost shock, which is indicative of no sub-
stantial real rigidities in pricing. In fact, pooling all categories of goods (target groups), pass-through seems almost complete, with the estimated $\beta_1$ coefficient almost equal to one and significant at the 1% level. Later, when developing the structural framework for counterfactual analysis in section 3.4, we focus exclusively on a single product category, shirts, to ensure meaningful quality comparisons. For that purpose, columns (2) and (4) list very similar results when the sub-sample is restricted to shirts. Remarkably, when only locally produced goods (made in Russia) are considered in columns (5) through (8), the pass-through coefficients are almost everywhere insignificant and hardly point in one robust direction.

Together with the fact that exchange rate movements are exogenous cost shocks from the vantage point of an individual retailer, these findings lend additional support to the causal interpretation of these results: consistent with Table 3.4 and apart from potential strategic complementarity considerations, the prices of Russian goods should be much less sensitive to exchange rate fluctuations. If all of our main results were driven by some aggregate income shock story, we should not expect to see such different outcomes for Russian and imported items.

### 3.4 Model

#### 3.4.1 Overview

Having documented that (1) there is incomplete pass through in the aggregate price index, and (2) there is a reallocation towards lower cost goods, and (3) there is a reallocation towards lower quality goods, we formulate a theoretic framework that speaks to all of these stylized facts.

The basic intuition of the model must rationalize the fact that there is a reallocation towards goods that are low cost, but also low quality. In the apparel industry, a low cost good can be inexpensive to produce because it is produced by an efficient firm in a low cost location, because it uses cheaper materials, or both. In a competitive industry, it is
reasonable that on average a low cost good must be cheaper or lower quality in some way on average, even if there is considerable dispersion for any given cost quantile.

If low cost goods also tend to be low quality goods, then these goods may not account for a large share of sales *ex ante* because they are less profitable. However, after a proportional exchange rate shock, high cost goods experience a much larger level increase in cost and therefore may experience a disproportionately larger decrease in profits and market share. High cost goods should be more insulated from the shock by their higher average quality. Yet if the variance of costs is relatively high and the variance of quality relatively low, then their higher quality will not be enough to keep them profitable. Low cost, low quality goods will increase their market share, especially relatively to the low *ex ante* share they enjoyed pre shock.

To formalize this intuition, we construct a simple model of oligopolistic competition with logit demand and match it to key moments of the data covering the periods prior to the shock. In the model, firms (individual products) enter and sell at wholesale cost to the monopolist. The monopolist charges a constant proportional markup over wholesale cost, so that firms actually face the residual demand curve of the consumers. On entry, firms draw a cost quality pair for their product from a fixed distribution; the steady state distribution of firms over cost quality states is determined by endogenous exit choices, as firms are faced with idiosyncratic payoffs to exit.

It should be made clear that individual SKUs, and not brands or the monopolist online retailer, are the main economic actors in this model. Based on the reduced form evidence on pass-through, the monopolist simply prices at a constant markup above wholesale cost. For this reason, as well as the fact that the monopolist’s problem is computationally difficult, we do not focus on the monopolist. In this version of the paper we refrain from focusing on brands as the economic actors simply because they exhibit huge variation in the quality of goods they offer: to model a brand as a product would drop key information about the
cost-quality distribution, while allowing brands to chose the set of goods they offer would create an intractably large state space.

We model the exchange rate shock as increasing the entire cost distribution proportionally to the depreciation in the ruble, with no effect on income as suggested by our reduced form evidence. In the new long run steady state, we find substantial reallocation towards low cost goods: the lowest quartile increases its share of firms by 10 percent, while higher quartiles decrease their shares by between 17 and 43 percent. We also construct the model’s predicted aggregate price index as a measure of model fit. The fixed-quantity price index (with quantity shares fixed to pre-shock levels) increases by only about 4%, which is roughly equal to the price index constructed from data alone.

Adding in the quality dimension better explains the pattern of increasing low cost goods share after the shock than a model with cost heterogeneity alone. Consider a model with cost and quality heterogeneity: the high quality firms are able to charge higher markups since they have larger positive demand shifters, which in turn makes other firms’ residual demand curves more inelastic, allowing them to charge higher markups. If high quality firms exit, then the competitive environment induces a general reduction in the markups of the remaining firms. In the model with only cost heterogeneity, the absence of this second order effect implies that the lowest quartile increases its share by only 6 percent. Evidently, medium cost, medium quality firms are most strongly affected by the second order effect, so that they lose relatively more—and low cost, low quality firms gain more—in the model with quality heterogeneity.

The model also generates new insights about the true effects of the exchange rate depreciation on consumer welfare. The model without quality heterogeneity implies a roughly 14% decrease in welfare following the shock, while the model with quality heterogeneity implies an almost 21% decrease in welfare. The model we specify is similar in spirit to most dynamic oligopoly models in the applied IO literature, starting with Ericson and Pakes (1995). In notation and exposition we closely follow Weintraub et al. (2008).
3.4.2 Notation and timing

The industry evolves over discrete time periods \( t \in \mathbb{N} \) and an infinite horizon. Brands that enter draw a state \( x \) from an invariant, discrete distribution \( F \) over all possible states \( A \), and keep that state until they exit. Firm \( j \)'s state is a cost quality pair for the single good it sells, \( x_j = (c_j, \lambda_j) \).

Define the industry state \( s_t \) to be a vector enumerating how many firms there are at each state \( x \in A \) in each period, so that the aggregate state space is \( \bar{S} = \{ s \in \mathbb{N}^\infty | \sum_{x \in A} s(x) < \infty \} \). For each \( j \in S_t \), define \( s_{-j,t} \in S \) to be the state of the competitors of firm \( j \), so that \( s_{-j,t}(x) = s_t(x) - 1 \) if \( x_{jt} = x \) and \( s_{-j,t}(x) = s_t(x) \) otherwise.

Firms earn profits each period on a spot market, with single period expected profit denoted by \( \pi(x_{jt}, s_{-j,t}, \theta) \). Profits will derived from demand and marginal cost primitives, indexed by parameter \( \theta \). New firms choose whether to enter and pay a fixed cost of entry \( \kappa \); incumbent firms observe a firm-time specific shock \( \phi_{jt} \) and decide whether to exit.

In each period, timing is as follows:

1. Incumbent firms observe their sell-off values and make exit decisions
2. The number of entrants is determined; entrants pay the fixed cost \( \kappa \)
3. Incumbent firms (even those that have committed to exit) compete in the spot market and receive profits
4. Exiting firms exit and receive scrap values, and new entrants enter and draw states from the \textit{ex ante} distribution.

3.4.3 Model primitives and assumptions

We assume that demand for goods is logit, marginal costs are constant and perfectly observed, and that prices are the Nash equilibrium of a Cournot pricing game. We further
assume that when brands wholesale to the monopolist, the simple heuristic that firm uses to set retail prices is to set a constant markup $\gamma$ over the wholesale cost $w_{jt}$, so $p_{jt} = \gamma w_{jt}$.

As usual, utility to consumer $i$ from consuming firm $j$’s product is:

$$U_{ijt} = \alpha p_{jt} + \lambda_j + \epsilon_{ijt}$$
$$U_{i0t} = \lambda_0 + \epsilon_{ijt}$$

Where the errors $\epsilon_{ijt}$ are distributed type II extreme value, giving the standard expression for market shares:

$$\sigma_{jt} = \frac{\exp(\alpha p_{jt} + \lambda_j)}{\exp(\lambda_0) + \sum_k \exp(\alpha p_{kt} + \lambda_k)}$$

Where $\sigma_{jt}$ denotes the firm $j$’s share of the market at time $t$. On entry, brands draw a constant marginal cost and quality pair. They observe the aggregate industry state and set wholesale prices accordingly, choosing their wholesale price $w_{jt}$ to solve:

$$\max_{w_{jt}} \sigma_{jt}(\gamma w_{jt})(w_{jt} - c_j)$$

Profits for $j$ are given as $\pi_{jt}(p_{jt}^*)$, where $p_{jt}^*$ are the prices that satisfy a static Nash equilibrium.

We assume that the scrap values $\phi_{it}$ are iid, with finite expectation and well-defined density functions over $R_+$. When matching the model to the data, we will pick the exponential distribution.

Finally, we assume that there are an asymptotically large number of potential entrants who play a symmetric mixed entry strategy, as in [Weintraub et al. (2008)]. They prove that this results in a Poisson-distributed number of entrants. The expected number of firms entering at industry state $s_t$ is denoted by $\delta_{s_t}$; the expected entry rate will be endogenously determined and satisfy a zero expected discounted profits condition.
3.4.4 Equilibrium

The data is assumed to be generated by a pure strategy Markov perfect equilibrium, where firms play symmetric strategies (that is, conditional on state, firms’ strategies are identical.) Continuing to follow the notation of Weintraub et al. (2008), firms follow an cutoff-rule exit strategy: there is a function \( \rho \) such that \( j \) exits at time \( t \) if and only if the randomly drawn scrap value exceeds this cutoff, \( \phi_{jt} \geq \rho(x_{jt}, s_{-j,t}) \). Crucially, because the state is two-dimensional, cutoffs are not monotonically decreasing in cost (although they are conditional on quality.) Finally, the entry rate function \( \delta(S_t) \) determines the Poisson average entry rate conditional on the aggregate state \( S_t \).

The value function \( V(x, s|\rho', \rho, \delta) \) is the expected NPV for a firm at state \( x \) when its competitors’ state is \( s \), given that its competitors each follow common strategy \( \rho \):

\[
V(x, s|\rho', \rho, \delta) = E_{\rho', \rho, \delta} \left[ \sum_{k=t}^{\tau_j} \beta^{k-t} \pi(x_{jk, s_{-j,k}}) + \beta^{\tau_j-t} \phi_{j, \tau_j}|x_{jt} = x, s_{-j,t} = s \right]
\]

\( j \) is the index of a firm at state \( x = (c, \lambda) \) at time \( t \), \( \tau_j \) is a random variable giving the optimal stopping time, and the expectation is over the firm’s own strategy as well as the strategy of its competitors.

We assume a symmetric MPE with positive entry rates. The full MPE comprises strategies \( \rho \) and an entry rate \( \delta \) such that

1. Incumbent firm strategies represent an MPE:

\[
\sup_{\rho'} V(x, s|\rho', \rho, \delta) = V(x, s|\rho, \rho, \delta)
\]

2. At each state, entrants have zero expected discounted profits and \( \lambda > 0 \):

\[
\beta E_{\rho, \delta, F} [V(x, s_{-j,t}|\rho, \delta)|s_t = s] - \kappa \leq 0
\]
3.5 Estimation

Our data contains information on hundreds of brands and thousands of products. Since even fitting the MPE is intractable in such an environment, we take an alternative approach. We assume that the data pre-shock is generated by firms playing Oblivious Equilibrium (OE) strategies. We then pick parameters and simulate data from the model, and match key simulated moments to moments in the data. Once we have matched moments, we can do experiments by altering parameters and using the same simulation mechanisms.

Oblivious Equilibrium is a solution concept pioneered by Weintraub et al. (2008) to deal with the problem of simulating data from industries with dozens or even hundreds of firms that are still plausibly competing oligopolistically. In their seminal work on solving MPE models, Bajari et al. (2007) demonstrate that simulating from an MPE model even with only 3 firms induces enormous computational burdens; moreover, problems of multiple equilibria grow in severity as the number of firms increases.

Oblivious Equilibrium assumes that all firms treat the aggregate state vector as being in its long run steady state. This simplifies the computational burden enormously: instead of needing to keep track of the state of every firm in the industry when solving its value function, a firm needs only pay attention to its own state. We take the Bajari et al. (2007) methodology one step further by using it in a simulated method of moments approach to estimate the model’s parameters.

Define \( \rho(x) \) to be symmetric, oblivious equilibrium strategy, \( \delta \) to be the oblivious entry rate, and the expected number of firms at state \( x \) at time \( t \) as \( \tilde{s}_t(x) = E[s_t(x)] \). Given the ex ante distribution function \( F \), there is a simple expression for the expected number of firms in each state:

\[
\lim_{t \to \infty} \tilde{s}_t(x) = \delta \int_{x \in A} \sum_{k>0} P(\phi > \rho(x))^k dF
\]
Let \( \tilde{s}_{\rho, \delta} = \lim_{t \to \infty} \tilde{s}_t(x) \). The oblivious value function is the expected NPV of a firm at state \( x \) following oblivious exit strategy \( \rho \) under the assumption that its competitors’ states are fixed at \( \tilde{s}_{\rho, \delta} \). It is given by:

\[
\tilde{V}(x|\rho', \rho, \delta) = E_{\rho'} \left[ \sum_{k=t}^{\tau_j} \beta^{k-t} \pi(x_{jk}, \tilde{s}_{\rho, \delta}) + \beta^{\tau_j-k} \phi_{\delta, \tau_j}|x_{jt} = x \right]
\]

The oblivious value function does not directly depend on its competitors’ dynamic strategies; however, since the aggregate state \( \tilde{s}_{\rho, \delta} \) does, the dependence is indirect. As in Benkard et al. (2008), we define an oblivious equilibrium as:

1. Incumbent firms optimize an oblivious value function:

\[
\sup_{\rho'} \tilde{V}(x|\rho', \rho, \delta) = \tilde{V}(x|\rho, \rho, \delta)
\]

2. At each state, entrants have zero expected discounted profits and \( \lambda > 0 \):

\[
\beta E_{\rho, \delta, F} \left[ \tilde{V}(x|\rho, \delta) \right] - \kappa \leq 0
\]

3.5.1 Moments

Define the distribution of scrap values by \( \Phi \). For a given set of parameters \( \{\alpha, \gamma, \lambda_0, F, \kappa, \Phi\} \) we can generate data from the Oblivious Equilibrium, using Bellman’s equation and value function iteration to solve the firm’s optimal stopping problem. There are two infinite dimensional probability distributions to be identified: the \textit{ex ante} distribution of costs and qualities \( F \), and the distribution of scrap values \( \Phi \).

To make the problem tractable, assume that the scrap value distribution is exponential with mean parameter \( K \). Further assume that \( F \) is distributed lognormal, with \( \log(X) \sim N(\mu, \Sigma) \). We discretize the distribution (at the marginal quantiles of the original conditional distribution) to make the state space discrete, with 25 cost quality combinations total. This
parameterization leaves us 10 objects (2 means in $\mu$ and 3 unique terms in $\Sigma$) to identify. $\gamma$ and $\lambda_0$ are identified directly from the data, while for the remainder we minimize the unweighted sum of the difference between the model’s simulated moments and the empirical moments in 3.1.

Table 3.1: Parameters and moments

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Interpretation</th>
<th>Identifying empirical moment</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>Coefficient on price in utility</td>
<td>Average elasticity</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Monopolist’s markup</td>
<td>Avg. markup over obs. wholesale cost</td>
</tr>
<tr>
<td>$\lambda_0$</td>
<td>Outside good utility</td>
<td>Normalize minimum quality to 0</td>
</tr>
<tr>
<td>$(\mu, \Sigma)$</td>
<td>Ex ante joint dist. of cost and quality</td>
<td>Discretized EDF</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>Entry cost</td>
<td>Number of firms entering</td>
</tr>
<tr>
<td>$K$</td>
<td>Mean scrap value</td>
<td>Rate of firm exit</td>
</tr>
</tbody>
</table>

3.6 Constructing moments from the data

The key moment we need to match in the data is the conditional joint distribution of cost and qualities, where the conditioning is on firm entry and exit. Although we have a measure of quality that we directly observe in the data and use to motivate our approach, better fabric composition is just one small part of why a good’s demand might be more inelastic. We estimate quality as a SKU specific fixed effect in a logit demand system. In particular, if an SKU has higher sales conditional on an identical price, we impute that good as having a high quality. Moreover, while we observe prices and average wholesale costs, we do not observe the marginal costs of the wholesalers themselves; this will also be recovered from the logit demand system.

Recovering quality from the data requires taking into account features of the environment that are not in our simple model. First, most brands are multiproduct; although substitution patterns may differ slightly within and between brands’ goods, we still use the simple (non-nested) logit to map closely to the structural model. However, when inverting the demand system to recover the brands’ marginal costs, we take account of the fact that firms selling
multiple goods will incorporate cross-elasticities of substitution across their own products when setting prices.

Second, as our data comes from an apparel retailer there is a strong seasonal component to some product lines; we therefore include month dummies to control for aggregate time-varying shocks. Finally, in order to use the Berry (1994) inversion and linear regression to estimate the qualities and costs, we must add in a product time specific demand shock to consumers’ utility. As usual, this shock is not observed by the econometrician but is observable to wholesalers when they make their pricing decisions, which leads to endogeneity, which we deal with using a number of instruments.

3.6.1 Demand

The monopolist firm sells \( J_t \) differentiated goods in month \( t \), which can be partitioned into \( B_t \) different brands. Let \( J_{bt} \) be the set of brand \( b \in B_t \) goods offered at time \( t \).

The upstream brands—the full set of which is denoted by \( B \)—are, as before, the principal decision makers in this model. Brands observe the full set of characteristics (qualities) for each good they can offer. They decide at what wholesale price (in rubles) to sell to the monopolist. Similarly to Nakamura and Zerom (2010), the downstream retailer will operate according to a heuristic rule; in this model, they charge a fixed percentage markup over the marginal cost, which we will recover from the data.

The value to consumer \( i \) of consuming good \( j \) at time \( t \) is given by:

\[
U_{ijt} = \lambda_j + \alpha p_{jt} + \xi_{jt} + \epsilon_{ijt}
\]

We assume \( \epsilon_{ijt} \) is distributed Type II extreme value to give a logit structure for demand. \( \xi_{jt} \) is a demand shock observable at the time brands choose the wholesale price, and is therefore endogenous with \( p_{jt} \) (which will simply be a constant multiplied by the wholesale price). \( \lambda_j \) will be recovered as a product SKU specific quality.
The value of the outside good is allowed to vary over time to capture time-varying aggregate shocks and seasonality:

\[ U_{i0t} = \lambda_t + \epsilon_{i0t} \]

Nested logit demand leads to the standard expression for the share of each product \( j \). Taking log differences (as in Berry (1994)) gives a simple linear expression:

\[ \ln \sigma_{jt}(\theta) - \ln \sigma_{0t}(\theta) = \alpha_{jt} + \lambda_j - \lambda_t + \xi_{jt} \]

Where \( \sigma_{jt}(\theta) \) denotes the share of good \( j \) at time \( t \) given parameters \( \theta \).

### 3.6.2 Supply

Let the monopolist’s constant markup over the wholesale cost be denoted \( \gamma \), so \( p_{jt} = \gamma w_{jt} \). This assumption is identical to the one made by Nakamura and Zerom (2010) in their paper on cost-shock pass-through for coffee manufacturers, except that their retail firms set prices a constant amount above wholesale cost, whereas our firm sets a constant percentage markup.

As in Berry et al. (1995), conditional on the set of products it offers in a season and the set of competitors it faces, each brand statically solves the profit maximization problem in every month:

\[
\max_{\{w_{jt}\}_{j \in J_b}, \{j \in J_b}} \sum_{j \in J_b} (w_{jt} - mc_{jt}) M_{st} \sigma_{jt}(\gamma w_{t}, \xi_{t}, \theta)
\]

Brand \( b \) will have a first order condition for each \( j \in J_b \):

\[
\sigma_{jt}(\gamma w_{t}, \xi_{t}) + \sum_{k \in J_b} (w_{kt} - mc_{kt}) \frac{\partial \sigma_{kt}(\gamma w_{t}, \xi_{t}, \theta)}{\partial p_t} = 0
\]
Define the $J_t$ by $J_t$ matrix entry by entry as $\Delta_{jk} = -\frac{\partial \sigma_k}{\partial p_j} 1[j, k \text{ owned by same } b]$. Then the vector of marginal costs of all wholesalers at time $t$, $mc_t$ is given as

$$mc_t(\theta) = w_t - \Delta(\gamma w_t, \xi_t, \theta)^{-1} \sigma(\gamma w_t, \xi_t, \theta)$$ (3.5)

### 3.6.3 Estimation and identification of the moment-generating model

Given the assumption $p_{jt} = \gamma w_{jt}$, if we observed time-varying wholesale costs then $\gamma$ could be identified by $\sum p_{jt} / \sum w_{jt}$. Instead, the data includes a weighted sum $w_j = \frac{1}{T_j} \sum_t q_{jt} w_{jt}$ where $T_j$ is the total number of time periods $j$ is observed. Thus we estimate $\gamma$ by:

$$\hat{\gamma} = \frac{\sum_j \frac{1}{T_j} \sum_t q_{jt} p_{jt}}{\sum_j w_j}$$ (3.6)

IV on the linear demand equation is used to identify the parameters $\theta \equiv \{\lambda_t, \lambda_j, \alpha\}$. Once again, the estimating equation for the demand curve is:

$$\ln \sigma_{jt}(\theta) - \ln \sigma_{0t}(\theta) = \alpha p_{jt} + \lambda_j - \lambda_t + \xi_{jt}$$

Taking a time and cross-sectional difference yields $\tilde{\xi}_{jt} \equiv (\xi_{jt} - \bar{\xi}_j) - \frac{1}{N} \sum_j (\xi_{jt} - \bar{\xi}_j)$, with $\bar{\xi}_j \equiv \frac{1}{T} \sum_t \xi_{jt}$. $\tilde{\xi}_{jt}$ is assumed orthogonal to observed price instruments $z_{jt}$.

The instrument $z_{jt}$ needs to vary with $j$ and $t$—an instrument that varies only with time, or cross-sectionally, will be differenced out in the first stage due to the presence of time and good fixed effects. We use a combination of instruments: first, lagged wholesale price is a valid instrument under the assumption that $\xi_{jst}$ is iid but that determinants of costs are persistent; second, different wholesalers are based in different countries, so good-specific exchange rates vary across goods so that these countries’ exchange rates might be relevant for marginal costs and hence, wholesale costs.
### 3.6.4 Moment-generating model results

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>OLS</th>
<th>IV1</th>
<th>IV2</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>-0.00012***</td>
<td>-0.00032***</td>
<td>-0.00049***</td>
<td>-0.00052***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>( j, t )</td>
<td>( j, t )</td>
<td>( j, t )</td>
<td>( j, t )</td>
</tr>
<tr>
<td>Instrument</td>
<td>lagged price</td>
<td>lagged price</td>
<td>exchange rate</td>
<td>exchange rate</td>
</tr>
<tr>
<td>( \alpha \cdot \gamma \cdot p(1 - s) )</td>
<td>0.416</td>
<td>1.25</td>
<td>2.08</td>
<td>2.26</td>
</tr>
<tr>
<td>(Mean price elasticity)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.045</td>
<td>0.554</td>
<td>0.758</td>
<td>0.7515</td>
</tr>
<tr>
<td>( N )</td>
<td>89058</td>
<td>69676</td>
<td>11857</td>
<td>9120</td>
</tr>
</tbody>
</table>

\( *** = 1\% \), \( ** = 1\% \), \( * = 5\% \) significance. Fixed effect \( j, t \) denotes fixed effects at the product SKU, season-month level.

Table 3.2: Structural demand parameter estimates

3.2 summarizes the results of the demand estimation. The inclusion of brand and time dummies goes far in solving the endogeneity problem between prices and unobserved (to the econometrician) quality; the average estimated price elasticity becomes larger than one, but not by much. Since we invert the demand system to recover marginal costs, it is crucial that the elasticities be reasonable, otherwise the marginal costs will be estimated too low—and perhaps even negative. The inclusion of instruments pushes the elasticity well above two, validating their efficacy.

In 3.1 we plot normalized marginal costs against normalized qualities (a random sampling of points is omitted). There is a very small, but nonetheless positive, relationship between cost and quality (coefficient of 0.01, \( p < 0.05 \)). Although the positive correlation seems marginal, it may well be large enough to induce the kind of selection our intuition suggests. Moreover, it is clear that there is a huge degree of quality variation among goods with the same costs—variation that will certainly be important for welfare calculations.

### 3.7 Results

After fitting the model to the pre-shock data, we estimate the fixed cost of entry as 173880 rubles, while the mean of the exponential distribution of scrap values is estimated as 43470 rubles.
rubles. Converted into dollars using the pre-shock exchange rate, these are roughly 5800\textit{USD} and 1450\textit{USD} respectively.

We are interested in comparing the performance of the model with quality heterogeneity to a more standard model with only cost heterogeneity. To that end, we fit a model with only cost heterogeneity to the data, and perform the same counterfactual on both models. Firms in the model with cost heterogeneity will have a fixed quality, set equal to the mean of qualities in the data. Our counterfactual is to double the brands’ marginal ruble costs to capture the effects of the exchange rate shock.
3.7.1 Model Fit

First, we compute a measure of model fit by looking at the change in the price index. To construct a quantity weighted price index equivalent to the one in 3.3.3, we weight by the quantities in the pre-shock period and use the old and new prices to compute price indices for each period; We then take the ratio of these indexes. Denote with $t$ objects pre-shock, and $t+1$ objects post-shock:

$$\Delta P = \frac{\sum_{x \in A} p_{t+1} \sigma_t(x) \hat{s}_t(x)}{\sum_{x \in A} p_t \sigma_t(x) \hat{s}_t(x)}$$

With only cost heterogeneity, the price index exhibits incomplete pass-through, with $\Delta P = 1.099$—the price index rises roughly 10%. As expected, with quality heterogeneity the price index increase is dampened: we find that $\Delta P = 1.043$, an increase of roughly 4%. This number is surprisingly close to the data despite not attempting to match this moment.

We also compute the average within-state change in prices for both models by taking the ratio of pre- and post-shock prices at each state, and then taking the simple average over those prices. The quality heterogeneity model exhibits within-state average price increases of 17.9% while the model without quality heterogeneity exhibits average price increases of 17.4%. Since we do not observe the marginal costs of the wholesalers themselves it is difficult to determine whether this is reasonable; we present it for completeness and to highlight the fact that in our logit model, markups do indeed adjust.

3.7.2 Counterfactual

To get a sense of whether or not our model can deliver reallocation towards low cost, low quality goods, we show how the distribution of firms in each cost state changes post shock. For the model with no quality heterogeneity, the cost quartile completely describes a firm’s position in the distribution; for the model with heterogeneity, the cost quartile is the marginal distribution integrating over the distribution of qualities in that quartile.
Results are presented in 3.3. In the leftmost column are the discretized states used in computation, at the pre-shock levels. The first two columns present (1) the initial distribution of firms across states and (2) the ratio of the fraction of firms in that state post cost shock to the fraction of firms in that state pre cost shock. The last two columns present analogues for the model with quality heterogeneity, where the distribution over costs is now the marginal distribution (integrating over the quality dimension.) Notice that for the lowest cost level (marginal cost of 146.09 rubles) there is a 9 percent increase in the number of firms in the model with quality heterogeneity, and only a 6 percent increase in the number of firms in the model without quality heterogeneity.

There are two conclusions to be drawn from this analysis: first, since cost and quality are positively correlated in the data, the model can indeed generate a redistribution towards low cost, low quality goods. The introduction of a flexible second dimension of good heterogeneity offers a straightforward and intuitive solution to the question of why lower quality goods seem to benefit during a depreciation with no income shock. Second, the model with quality heterogeneity can actually induce a greater reallocation towards lower cost quartiles. As previously mentioned, a mechanism in the model that can rationalize this fact is the second-order impact of quality heterogeneity on the competitive environment.

Table 3.3: Reallocation towards low cost goods

<table>
<thead>
<tr>
<th>Marginal cost</th>
<th>No quality het.</th>
<th>Quality het.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Initial dist.</td>
<td>New/Initial</td>
</tr>
<tr>
<td>146.09</td>
<td>0.37</td>
<td>1.06</td>
</tr>
<tr>
<td>305.44</td>
<td>0.23</td>
<td>0.82</td>
</tr>
<tr>
<td>590.89</td>
<td>0.18</td>
<td>0.67</td>
</tr>
<tr>
<td>2884.25</td>
<td>0.21</td>
<td>0.77</td>
</tr>
</tbody>
</table>

Finally, to compute the change in welfare, we use the standard logit formula for the consumer surplus to market participation:

\[ W = \log \left( \sum_j \exp(\alpha_p + \lambda_j - \lambda_0) \right) \]
Taking $\Delta W$, the ratio of post to pre shock welfare, we find that, as expected, the model without quality heterogeneity predicts lower welfare losses after the exchange rate shock. The model with only cost heterogeneity has $\Delta W = 0.857$, a roughly 14% decrease in welfare, while the model with both cost and quality heterogeneity has $\Delta W = 0.791$, a roughly 21% decrease in welfare. Interestingly, the model with both cost and quality heterogeneity exhibits a smaller increase in the price index, but a fall in welfare that is 50% larger than the model without such heterogeneity. Quality heterogeneity evidently dampens the effect of the cost shock on the price index while simultaneously increasing the welfare cost to consumers through a lower quality selection of goods.

### 3.8 Conclusion

We use a novel online retail dataset that spans Russia’s enormous currency depreciation in late 2014 to analyze the role of compositional shifts in product offerings for consumer welfare and price dynamics. We document in the data that there is a reallocation towards relatively low cost and low quality goods after the shock. We take care to show that this reallocation is not driven by an income shock or “flight from quality”. For models with a single dimension of product heterogeneity this represents a puzzle: the highest quality firms and lowest cost foreign firms should remain after a cost shock, while low quality and high cost firms should exit.

To make progress on resolving this question, we construct a model of demand and firm dynamics where consumers value low prices and high qualities, and firms draw product cost and quality from a joint distribution on entry. A positive correlation between marginal cost and quality can explain quality downgrading as a byproduct of high cost, high quality firms exiting. We verify that the correlation holds in the data and calibrate the model to pre-shock moments. A counterfactual cost shock shows that high cost firms disproportionately exit
while the share of low cost, low quality firms increases, which has sizable repercussions for consumer welfare.

The paper shows how a richer model of product cost and quality heterogeneity can explain the quality downgrading observed in the data. It refrains from proving general statements about the conditions on the joint distribution of cost and quality that would be necessary to ensure quality downgrading in a crisis. Moreover, the model generates rich predictions on how the distribution of markups change in response to a cost shock; indeed, we rely on a consequence of those predictions when arguing for why the model with cost and quality heterogeneity induces a greater reallocation towards lower cost goods than the model with cost heterogeneity alone. A more thorough understanding of the patterns in markups and pass-through that can be generated by introducing meaningful quality heterogeneity is a fruitful avenue for future research.
3.9 Bibliography


Figure 3.2: Overlapping Generations of Goods

Note: This figure shows the seasonal and short-lived nature of apparel goods in the data. Time is shown at a quarterly frequency on the horizontal axis and the percentage of revenue generated by goods of various generations is displayed on the vertical axis. The essence of the industry dictates that almost all goods live for two or at most three quarters of a given year.
Note: This figure shows the normalized log usd/rub exchange rate (black solid line), the mean monthly (red dashed line), inventory-weighted mean monthly (blue short-dashed line), and purchase quantity-weighted mean monthly deseasonalized wholesale prices of all SKUs (green long-dashed line) series across time.
Figure 3.4: Price Indexes

Note: This figure displays the apparel price indexes for imported and locally produced (Russian) goods. Both series are normalized to 100 in 2013m1. The vertical red lines delineate the active phase of Russia’s devaluation crisis.
Figure 3.5: **Price Adjustments**

(a) Frequency of Price Changes

(b) Weighted Frequency of Price Changes

**Note:** Panel (a) shows the percentage of goods that undergo price changes (either up or down) in any given month relative to the previous month; Panel (b) shows the sales-weighted fraction of price changes, which is equivalent to the expenditure share of SKUs with price adjustments.
Figure 3.6: Fabrics & Quality Index

(a) Shirt Fabric Types

(b) Quality Index for Shirts

Note: Panel (a) shows the fabrics composition for Shirts (sole material) across fall-winter (left) and spring-summer (right) seasons; Panel (b) shows the textile prices based quality index for imported (grey) and Russian (black) shirts across spring-summer seasons.
Figure 3.7: Demand Channel

(a) Regional Growth (2015)

Note: Panel (a) depicts regional GDP growth rates across Russian oblasts in 2015, with darker colors meaning higher economic growth; Panel (b) plots the estimated $\delta_t$ coefficients of equation 3.2 with 95% confidence intervals around them. Results for three distinct outcome variables over time are displayed: the log median regional purchase price (black), the log mean regional purchase price (grey), and the quantity-weighted fraction of premium sales. Time is measured on a monthly level and the vertical red line delineates the beginning of Russia’s currency crisis in 2014m11.
Table 3.4: Within-SKU Pass-through

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
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<th>(5)</th>
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<th>(7)</th>
<th>(8)</th>
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</thead>
<tbody>
<tr>
<td>( \Delta_{\tau_1}usdrub_t )</td>
<td>( 0.911*** )</td>
<td>( 0.474*** )</td>
<td>-0.448</td>
<td>-0.011</td>
<td>( [0.172] )</td>
<td>( [0.142] )</td>
<td>( [0.881] )</td>
<td>( [1.484] )</td>
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<tr>
<td>( \Delta_{\tau_2}usdrub_{t-\tau_1} )</td>
<td>-0.125</td>
<td>-0.016</td>
<td>-0.552</td>
<td>0.034</td>
<td>( [0.192] )</td>
<td>( [0.322] )</td>
<td>( [0.726] )</td>
<td>( [1.081] )</td>
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<tr>
<td>( \Delta_{\tau_1}eurrub_t )</td>
<td>( 1.083*** )</td>
<td>( 0.624*** )</td>
<td>-0.111</td>
<td>2.004*</td>
<td>( [0.160] )</td>
<td>( [0.218] )</td>
<td>( [0.807] )</td>
<td>( [1.156] )</td>
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<tr>
<td>( \Delta_{\tau_2}eurrub_{t-\tau_1} )</td>
<td>-0.262</td>
<td>-0.255</td>
<td>-0.462</td>
<td>-1.216</td>
<td>( [0.193] )</td>
<td>( [0.351] )</td>
<td>( [0.635] )</td>
<td>( [1.016] )</td>
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<td>1,303</td>
<td>1,106</td>
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<td>( R^2 )</td>
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<td>0.355</td>
<td>0.479</td>
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<td>0.280</td>
<td>0.353</td>
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<td>0.442</td>
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</table>

Note: This table presents pass-through coefficient estimates at the first and second rounds of price adjustment respectively, estimated from regression 3.4. The outcome variable is the change in the log ruble price of a good, conditional on price adjustment. All specifications include SKU fixed effects and standard errors [in brackets] are clustered at the SKU-level to allow for serial correlation across time. The estimation results are based on daily observations between Jan 1, 2012 and April 1, 2015. ***,**,* indicate significance at the 1%, 5% and 10% levels, respectively.